Fintech and Racial Barriers in Small Business Lending*

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Abstract

This paper investigates the role of fintech lenders in reducing racial barriers in small business lending. Using a nationwide linked database of Paycheck Protection Program (PPP) loans and Yelp-listed restaurants, we document that minority-owned businesses are more likely to use fintech lenders than traditional lenders. In a simple two-sided matching game model, this phenomenon can be generated through a "fintech-minority matching value channel" and a "lending relationship channel". Empirically, we find supporting evidence for both channels. First, we find evidence suggesting that fintech-minority matches generate higher matching values than other matches. Second, we find that minority-owned restaurants are less likely to have lending relationships and this is positively associated with fintech usage. Estimating an empirical matching model, we find that the fintech-minority matching value channel is 0.69 times as important as the lending relationship channel.

Key Words: Racial Barriers, Minority-owned Businesses, Paycheck Protection Program, Small Business Lending, Bank Lending, Nonbank Lending, Fintech
JEL Classification: D63, G2, G21, G28, H25, M14

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Introduction

Racial disparities in the traditional small business credit market is a well-documented phenomenon in the U.S. (Bates (1997)).[1] With the recent development of more automated and anonymized lending technologies, or fintech lenders (Goldstein et al. (2019), Berg et al. (2021)), it comes a natural question: do fintech lenders serve minority-owned businesses who are in the blind spots of traditional lenders? Given the importance of this question, empirical studies are scarce, probably due to the lack of data on fintech loans in small business lending. In this paper, we attempt to fill the gap by providing novel evidence on the existence and mechanisms of fintech lenders in reducing racial barriers in small business lending.

There are at least two reasons that fintech lenders can mitigate racial barriers in the credit market.[2] First, it is possible that fintech lenders are more valuable to minority borrowers. The feature of few in-person interactions of fintech lenders (Buchak et al. (2018), Fuster et al. (2019)) can lower down communication costs and expectation of discrimination. Second, there can be racial disparities in previous lending relationships in the banking system.[3] The usage of alternative data allows fintech lenders to reduce the reliance on soft information (Berg et al. (2020), Di Maggio and Yao (2021)) which is a crucial role of lending relationships (e.g. Berger and Udell (1995), Liberti and Petersen (2019) for a survey), and thus benefit minority borrowers who do not have prior lending relationships.

Using a matching game framework between borrowers and lenders, this paper aims to answer the following questions. Are minority borrowers more likely to be matched with fintech lenders? Do fintech-minority matches generate higher matching values than other types of matches (the "fintech-minority matching value channel")? Are there racial disparities in previous lending relationships and how is this related to fintech usage (the "lending relationship channel")? What is the relative importance of the two channels?

We study these questions in the context of the Paycheck Protection Program (PPP), a

[1] Other papers include Cavalluzzo and Cavalluzzo (1998), Cavalluzzo et al. (2002), Blanchflower et al. (2003), Cavalluzzo and Wolken (2005), Blanchard et al. (2008), Asiedu et al. (2012), Bates and Robb (2013).

[2] There can be a third reason that minority-owned businesses are more likely to be located in regions with limited banking resources as documented in Erel and Liebersohn (2020). We address this channel by controlling for geographic information in our empirical analysis.

[3] There is a large literature on lending relationships, including Leland and Pyle (1977), Diamond (1984), Petersen and Rajan (1994), Yasuda (2005), Bharath et al. (2007), Bolton et al. (2016), Beck et al. (2018).

key component of the Coronavirus Aid, Relief, and Economic Security (CARES) Act enacted on April 3, 2020.[4] We link PPP recipients to restaurants listed on Yelp.com, generating a nationwide sample of 98,000 restaurants, which offers several advantages. First, it allows us to build a proxy for minority-owned businesses using the food type from Yelp.com to address the data limitation of missing race and ethnicity information for almost 80% of the sample. Second, in essence, all restaurants are eligible for the PPP, which means no variation resulting from regulation.[5] Third, the Yelp rating of the restaurant, as a proxy for operational performance, provides a way to gauge the difference in matching values.

To describe the relationship between borrowers and lenders in the PPP, we first develop a simple two-sided matching game model. In the model, we show that two types of barriers can lead to racial disparities in fintech usage. First, if fintech-minority matches generate a higher matching value than fintech-non-minority matches, a larger share of minority borrowers are matched with fintech lenders in equilibrium. Second, if a smaller share of minority borrowers have prior lending relationships, more of them turn to fintech lenders because of the crowding-out effect by borrowers with lending relationships in the banking system (Li and Strahan (2021), Amiram and Rabetti (2020), Duchin et al. (2021)).

One important empirical implication of the model is that we can use an observed variable, in our case the Yelp rating, to gauge the difference in the matching values that is hard to measure directly. Suppose we find evidence of a more negative minority-non-minority rating gap for fintech lenders, it suggests that fintech-minority matches generate a higher value to compensate for the lower rating. Phrased differently, if the minority-non-minority rating gap of the marginal borrowers using fintech lenders is smaller than that of the marginal borrowers using traditional lenders, it means that fintech lenders are more inclusive and easier to use for minority borrowers.

In the empirical analyses, we start by showing evidence of a positive and significant association between minority ownership and fintech usage. Black-, Asian-, and Hispanic-owned restaurants are more likely to use fintech lenders by 9.17%, 8.44%, and 1.22% respectively,

[4] More information on the PPP program is provided in the Appendix. See also https://www.sba.gov/funding-programs/loans/covid-19-relief-options/paycheck-protection-programext

[5] For most industries, the eligibility requirement is either meeting the SBA size standards for small businesses or less than 500 employees. For the Accommodations and Food Services sector, the eligibility is that the number of employees is fewer than 500 at each location.

with the sample mean being 9%. Observed business characteristics, including *Employment Size*, *Franchise* and *Business Type*, account for 12% of the variation in the fintech usage for Black- and Asian-owned restaurants and 28% for Hispanic-owned ones. Across-city differences account for 32% of the variation for Black-owned and 16% for Asian-owned restaurants. For the Hispanic group, we observe limited racial disparities in fintech usage after controlling for across-city differences.

Then, we show supporting evidence for the fintech-minority matching value channel. We document that the minority-non-minority rating gap (racial gap for short) is more negative for fintech lenders. According to our model, this suggests that fintech lenders, compared to traditional lenders, are more valuable to minority borrowers. Exploring heterogeneity among lenders, we find that the four largest banks in our sample, JPMorgan, Bank of America, Wells Fargo, and U.S. Bank, do *not* have a large racial gap in ratings. In contrast, relatively smaller banks have pronounced racial gaps.

Regarding whether the effect comes from the demand or supply side, we find that factors on both sides can influence the level of the racial gap. On the borrower side, the borrower's business capital can be a type of soft assets that serve the role of collateral (Hochberg et al. (2018)). We find a smaller difference in the racial gap between fintech and traditional lenders for borrowers with higher levels of business capital that is proxied by the total number of ratings of the restaurant. On the lender side, geographic distance between borrowers and lenders affects the use of soft information (Agarwal and Hauswald (2010)). We find that the difference in the racial gap is smaller for more geographically focused lenders.

As to the lending relationship channel, we also find suggestive evidence for it. We find that minority-owned businesses are less likely to have previous lending relationships. Moreover, our evidence shows that borrowers without lending relationships are more likely to gain a PPP loan through fintech lenders. Interestingly, after controlling for lending relationships, the positive association between minority ownership and fintech usage only changes slightly. This suggests that lending relationships cannot fully explain why minority borrowers are more likely to use fintech lenders.[6]

[6]Also notice that in our model, if there are only racial disparities in terms of lending relationships, we will not observe the existence of a racial gap in ratings of borrowers using fintech versus traditional lenders.

Results are consistent when we restrict to a matched sample using business locations, food price range, and other business characteristics as matching covariates. Results are also robust when controlling for city×month fixed effects and approval date fixed effects. We rule out several non-technology-related features of fintech lenders by studying other lender classifications. We do not find a similar pattern in lender usage and rating gaps for first-time banks (banks did not previously participate in SBA 7(a) or 504 programs), community development financial institutions and corporations, credit unions, non-federally insured lenders, or savings & loan associations.

Finally, we quantify the relative importance of the two channels using a more structured approach. We employ the Fox (2018) estimator that is adapted to the borrower-lender matching in Schwert (2018). The Fox (2018) estimator has the strengths of taking into account the interactions among different players in the matching game and no requirement of data on transferred payments. Consistent with the regression analysis, we find positive coefficients for both channels. The positive coefficient on the interaction between the fintech lender and minority borrower indicators means that fintech-minority matches generate higher levels of matching values than other matches. Similarly, the positive coefficient on the lending relationship dummy means the match between a pair of a borrower and a lender with prior relationships has higher matching values than matches without prior relationships.

Moreover, we find that the "fintech-minority matching channel" is 0.69 times as important as the "lending relationship channel" in the 2020 PPP and 0.49 times as important in 2021. In the empirical matching model, we also control for the geographic distance between the borrower and the lender to account for the location channel. In addition, we control for the interaction between the fintech lender indicator and the borrower's rating to capture rating-based sorting. Taken together, the estimation shows that after controlling for geographic and sorting reasons, both the "fintech-minority matching channel" and the "lending relationship channel" are important, with the latter contributing more to the equilibrium outcome.

Overall, our findings suggest that there are race-dependent blind zones in the traditional small business lending market. We find that minority-owned businesses are more likely to use fintech lenders in the PPP program. More importantly, we explore how fintech lenders can mitigate racial disparities and find evidence on a "fintech-minority matching value channel" and a "lending relationship channel".

The PPP setting provides a good laboratory for several reasons. First, the loan terms are fixed by the Small Business Administration, which rules out that fintech lenders attract different borrowers using more flexible loan terms. Second, all small businesses are hit by the Covid-19 shock almost simultaneously, and applications start on the same day for all borrowers. This controls for the impact of the business development stage on fintech usage. Since the Covid-19 crisis is an economy-wide shock, the high demand for credit, plus the extremely low interest rate and the possibility of forgiveness, provides strong incentives for any borrowers to participate.[7] Third, as discussed in several papers (Amiram and Rabetti (2020), Balyuk et al. (2020), Duchin et al. (2021)), because the credit risk concern is fully transferred to the government, differences in the use of fintech lenders by minority and non-minority borrowers cannot be explained by the risk management of lenders.

Our paper contributes to the literature on racial disparities in the small business credit market in several ways. First, we provide novel evidence to the scant literature on this important topic. Despite that there is a large body of literature on the PPP program,[8] few papers look at racial disparities. Earlier studies conduct county/zip code-level analysis (Fairlie and Fossen (2021b), Erel and Liebersohn (2020), Wang and Zhang (2020)) or use the subsample with race and ethnicity information (Atkins et al. (2021)). Two contemporaneous papers, Chernenko and Scharfstein (2021) and Howell et al. (2021), like our paper, link the PPP dataset with other data sources to create a firm-level minority measure, which allows for a richer set of findings. Using a different research design, our evidence is largely consistent with the findings in the contemporaneous papers and provides further support for the existence of racial disparities in the PPP.

Second, we look at racial disparities through the lens of the operational performance

[7] Admittedly, some borrowers might be rejected after the loan application, but the survey results in Bartik et al. (2020) suggest that inability to submit an application accounts for two-thirds of the loan denials and in total only 8% of the loan applications are rejected by the SBA.

[8] See Berger and Demirgüç-Kunt (2021) for an early survey. Examples include Bartik et al. (2020) and Granja et al. (2020) on accessing the allocation, Autor et al. (2020) on sustaining employment, Balyuk et al. (2020) and Cororaton and Rosen (2021) on reputational and disruption costs of receiving PPP funds, Duchin et al. (2021) on favoritism of lending relationships, Humphries et al. (2020) on information frictions in the loan application procedure, Bartlett III and Morse (2020), Berger et al. (2021b), Denes et al. (2021) on real effects of the program, Berger et al. (2021a) and Duchin and Hackney (2021) on political influence on the fund allocation.

measure, which, to the best of our knowledge, is not investigated in other papers. We show a specific type of financial inclusion role of fintech lenders that they are more inclusive to the lower range of minority-owned businesses whose productivity may be harmed by the lack of SBA funding previously (Krishnan et al. (2015), Brown and Earle (2017)). In this sense, our evidence links the racial disparities in the credit market to real-economy outcomes.

Third, we put emphasis on the channels through which fintech lenders can address the issue of racial disparities. Our paper highlights a borrower-side benefit of fintech lending for the minority group. A more automatic lending process lowers the level of racial barriers to approaching lenders. Other contemporaneous papers focus on the lender side and show that an anonymized lending procedure can reduce taste-based discrimination (Howell et al. (2021), D'Acunto et al. (2020)). In addition to the channel captured by higher matching values between fintech lenders and minority borrowers, we also show the channel on racial disparities in lending relationships and quantify the relative importance of different channels.

Our paper is also related to the nascent literature on fintech lending, in particular, on the financial inclusion role of fintech lenders (Jagtiani and Lemieux (2018)) and the relationship with traditional lenders (Cumming et al. (2019), Gopal and Schnabl (2020), Beaumont et al. (2021), Donaldson et al. (2021)), demand side factors such as misreporting (Griffin et al. (2021)) and trust in the banking system (Yang (2021)) and supply side factors (Ben-David et al. (2021)) affecting fintech lending, and racial biases in the lending procedure (Bartlett et al. (2022); Fuster et al. (2020), Dobbie et al. (2021)). Our paper adds to the literature by providing novel evidence that fintech lenders extend the credit access to minority borrowers who are overlooked by traditional lenders.

The remainder of the paper proceeds as follows. Section I. presents a simple matching game model. Section II. describes the data sources, the sample, and summary statistics. Section III. provides regression results on the racial disparities in the PPP and fintech usage. Section IV. presents evidence from a semiparametric matching model. Section V. concludes.

I. A Simple Matching Game Model

In this section, we develop a simple transferable utility matching game model a la Azevedo and Hatfield (2018) to describe the matching process between borrowers and lenders in the PPP program. The model illustrates two potential channels of racial disparities that can be alleviated by fintech lenders: higher matching values for fintech-minority matches and racial disparities in previous lending relationships.

There can be several reasons for higher matching values for minority borrowers when matched with fintech lenders than with banks. For example, a less bureaucratic process and fewer human contacts in a fintech loan application may be more beneficial to minority borrowers who are more likely to have language and culture barriers. It is also possible that minority borrowers have more negative previous experiences with banks and therefore have a higher utility gain from new technology-oriented lenders. On the lender side, it is much less costly for fintech lenders to reach any region, including those that are covered less by traditional financial institutions but with a larger minority population.

A smaller share of minority borrowers who have previous lending relationships can also be important to the racial disparities in the matching process. Previous lending relationships play a crucial role in the PPP (Li and Strahan (2021); Duchin et al. (2021)). For example, on the lender side, helping existing customers to survive the crisis may alleviate the debt overhang problem (Amiram and Rabetti (2020)). On the borrower side, the existing profile of the borrower can make it easier to navigate the application process. Without previous lending relationships, borrowers may be crowded out from the banking system to fintech lenders.

We present the basic model setup and the main results here. Further details on the assumptions, deviations, and discussions can be found in the Online Appendix D.

Model Setup. There are a group of fintech lenders with a mass of M^f and a group of banks with a mass of M^b. There are a group of minority borrowers with a mass of M^m and a group of non-minority borrowers with a mass of M^nwhose ratings follow the normal distribution $\gamma_i^m \sim N(\mu^m, \sigma^m)$, and $\gamma_i^n \sim N(\mu^n, \sigma^n)$ respectively. Empirical patterns presented in Figure 1 support a normal distribution of borrower ratings. An α fraction of borrowers possess lending relationships where α can be different for the minority and non-minority groups.

[INSERT FIGURE 1 AROUND HERE]

Payoff Function. The payoff function of a match between the borrower i and the lender j, $p_{i,j}(\gamma_i, \theta_{i,j})$, depends on the borrower's rating γ_i and a lender-borrower specific parameter $\theta_{i,j}$. The rating as an empirically observable variable entering the payoff function gives empirically testable predictions on otherwise unobserved matching values. In addition, it allows for rating-based sorting in the matching outcome. The lender-borrower specific parameter $\theta_{i,j}$, which can be race-neutral or race-dependent, reflects race dependent frictions in the matching process. We allow for an additional utility component from technology. That is the payoff is higher for matches with fintech lenders than matches with banks.

Simplification Assumptions. We make two assumptions for simplification purposes. Our main findings do not depend on the two assumptions. More discussions in the Online Appendix D.

(A1) A ω fraction of borrowers who possess previous lending relationships are matched with banks where ω is endogenously determined in the equilibrium.

(A2) The payoff function is of a linear functional form. $p_{i,j}(\gamma_i, \theta_{i,j}) = \gamma_i$ for borrowers matched with banks, and $p_{i,j}(\gamma_i, \theta_{i,j}) = \gamma_i + \theta_{i,j}\gamma_i$ for borrowers matched with fintech lenders.

Matching Game. Without loss of generality, we study a 1-lender-m-borrower matching game.[9] The borrower i chooses a lender to apply to with a transferred utility (price). If the lender j accepts the application from the borrower i, a match (i,j) happens and the lender gains the transferred utility and the borrower gains the total payoff $p_{i,j}(\gamma_i, \theta_{i,j})$ minus the transferred utility. If the lender j rejects the application from the borrower i, no match happens and no total payoff is generated. The borrower i may apply to another lender or renegotiate the offered transferred utility. If no lender is willing to accept the borrower for any transferred utility that leaves a non-negative payoff to the borrower, the borrower is

[9] In the PPP program, observations where a borrower is granted multiple loans are few. In our sample construction, fewer than 2% of the restaurants appeared to be associated with multiple loans. We exclude those observations from our analysis sample.

unmatched.

Equilibrium. In a competitive equilibrium, incentive compatibility constraint means that any deviation from either the borrower side or the lender side cannot achieve a higher payoff. The prices (transferred utilities) clear the market such that

$$p_{i,j}\left(\gamma_i, \theta_{i,j}\right) \geq p_{i,j'}\left(\gamma_i, \theta_{i,j'}\right) \text{ for } j' \neq j \text{ and } p_{i,j}\left(\gamma_i, \theta_{i,j}\right) \geq p_{i',j}\left(\gamma_{i'}, \theta_{i',j}\right) \text{ for } i' \in I \backslash I_j^* \tag{1}$$

Where I is the entire borrower set, and I_j^* is the optimal choice set of lender j.

Benchmark. In the benchmark case, we study the equilibrium when there are no racial barriers in the credit market. We make two assumptions on the parameters,

(1) The fraction of borrowers who possess lending relationships is the same for minority and non-minority borrowers. That is, $\alpha^m = \alpha^n = \alpha$.

(2) The payoff function is race-neutral. That is, $p_{i,j}(\gamma_i, \theta_{i,j}) = \gamma_i$ for both minority and non-minority borrowers matched with banks, and $p_{i,j}(\gamma_i, \theta_{i,j}) = \gamma_i + \theta\gamma_i$ for both minority and non-minority borrowers matched with fintech lenders.

We have a unique race neutral equilibrium. For borrowers who do not have previous lending relationships, those whose ratings are above the threshold $\underline{\gamma}\,(1+\theta)$ are matched with fintech lenders and those whose ratings are within the range of $\underline{\gamma}$ to $\underline{\gamma}\,(1+\theta)$ are matched with banks. For borrowers with previous lending relationships, a ω fraction of them are matched with banks. Other borrowers are unmatched. The matching threshold $\underline{\gamma}$ and the fraction of matched borrowers among those with previous lending relationships ω are determined by the following equations,

$$(1-\alpha)\left(M^m \int_{\underline{\gamma}(1+\theta)}^{\infty} f\left(x, \mu^m, \sigma^m\right) dx + M^n \int_{\underline{\gamma}(1+\theta)}^{\infty} f\left(x, \mu^n, \sigma^n\right) dx\right) = M^f$$

$$\omega\alpha\left(M^m + M^n\right) + (1-\alpha)\left(M^m \int_{\underline{\gamma}}^{\underline{\gamma}(1+\theta)} f\left(x, \mu^m, \sigma^m\right) dx + M^n \int_{\underline{\gamma}}^{\underline{\gamma}(1+\theta))} f\left(x, \mu^n, \sigma^n\right) dx\right) = M^b$$

Where $f(\mu^m, \sigma^m)$ and $f(\mu^n, \sigma^n)$ are the density functions of the rating distribution for the minority and non-minority borrowers respectively.

The reason that the matching threshold is the same for minority and non-minority borrowers is that the payoff function is the same for minority and non-minority borrowers. Incentive compatibility constraints equalize the price (transferred utility) paid by the marginal borrower to fintech lenders and to banks. Thus, the wedge between the rating of the marginal borrower is determined by the additional utility parameter θ: $\underline{\gamma_{b,nr}} = \underline{\gamma_f}(1+\theta)$. We present the incentive compatibility constraints here. More discussions in Online Appendix D.

$$\underline{\gamma_{b,nr}} - p_f = \underline{\gamma_{b,nr}} - p_b$$

$$\underline{\gamma_f}(1+\theta) - p_f = \underline{\gamma_f}(1+\theta) - p_b$$

$$\underline{\gamma_f}(1+\theta) - p_f = 0$$

$$\underline{\gamma_{b,nr}} - p_b = 0$$

In the benchmark case, our model has two main predictions. First, the same share of minority and non-minority borrowers are matched with fintech lenders relative to banks, given the same underlying rating distribution.[10] Second, while we allow for a wedge in ratings between borrowers matched with fintech lenders and with banks, we do *not* observe a difference in the minority-non-minority rating gap for borrowers matched with fintech lenders and with banks as we have the same matching threshold for minority and non-minority borrowers.

Fintech-Minority Matching Values. Now, we assume no racial disparities in previous lending relationships but race-dependent matching values (payoff functions). The assumptions on the parameters are,

(1) The fraction of borrowers who possess lending relationships is the same for minority and non-minority borrowers ($\alpha^m = \alpha^n = \alpha$).

(2) The payoff function is race-dependent. Setting the difference for banks to zero, we assume that $p_{i,j}(\gamma_i, \theta_{i,j}) = \gamma_i$ for both minority and non-minority borrowers matched with banks, and $p_{i,j}(\gamma_i, \theta_{i,j}) = \gamma_i(1+\theta^m)$ for minority borrowers and $p_{i,j}(\gamma_i, \theta_{i,j}) = \gamma_i(1+\theta^n)$ for non-minority borrowers matched with fintech lenders.

The mathematical presentation of the equilibrium is in the Appendix. As in the bench-

[10] The difference in the rating distribution is a source to generate rating-based sorting effects in the fintech usage between different groups of borrowers, which is not our focus here.

mark case, the additional utility from technology results in a higher matching threshold for fintech lenders than for banks. Unlike the benchmark case, the equilibrium is race-asymmetric in terms of the matching thresholds. The group of borrowers that have a higher additional utility from technology are willing to transfer a higher share of the total payoff to fintech lenders. This results in a smaller matching threshold of fintech lenders for that group of borrowers. Proposition 1 presents this result.

Proposition 1. In the case of race dependent matching values, the matching thresholds for minority-fintech, non-minority-fintech, minority-bank, and non-minority-bank matches in equilibrium satisfy,

$$\underline{\gamma_{mf}} = \frac{\theta^n}{\theta^m}\underline{\gamma_{nf}}$$

$$\underline{\gamma_{mb}} = \underline{\gamma_{nb}}$$

□

Proof in the Appendix.

Proposition 1 implies that when minority borrowers have a higher preference for technology than non-minority borrowers ($\theta^m > \theta^n$), the matching threshold with fintech lenders is lower for minority borrowers ($\underline{\gamma_{mf}} < \underline{\gamma_{nf}}$). Moreover, a lower matching threshold for minority-fintech matches implies a more negative minority-non-minority rating gap of the marginal borrower matched with fintech lenders compared to the marginal borrower matched with banks, which can be translated into a parallel difference in the expected mean of matched pairs. Corollary 1 presents this result.

Corollary 1. The minority-non-minority rating gap in the matching thresholds is more *negative* (*positive*) for fintech lenders if minority borrowers have a *higher* (*lower*) matching value with fintech lenders.

$$\left(\underline{\gamma_{mf}} - \underline{\gamma_{nf}}\right) - \left(\underline{\gamma_{mb}} - \underline{\gamma_{nb}}\right) \lesseqgtr 0 \ if \ \theta^m \gtreqless \theta^n$$

Furthermore, suppose that the underlying distribution is the same for minority and non-minority borrowers, i.e., $\mu^m = \mu^n = \mu$ and $\sigma^m = \sigma^n = \sigma$, then the minority-non-minority rating gap between fintech lenders and banks in the conditional expectation of the rating levels equals $\sigma\left(G\left(\frac{\gamma_{mf}-\mu}{\sigma}\right)-G\left(\frac{\gamma_{nf}-\mu}{\sigma}\right)\right)$, where $G\left(x\right)=\frac{\varphi(x)}{\Phi(-x)}+\frac{\varphi(x)-\varphi(\widetilde{\gamma})}{\Phi(x)-\Phi(\widetilde{\gamma})}$, with $\widetilde{\gamma}=\frac{\gamma_{mb}-\mu}{\sigma}$ and $\varphi(\bullet)$ and $\Phi(\bullet)$ as the density and cumulative distribution functions of the standard normal distribution respectively. □

Proof in the Appendix.

Both predictions of the model are affected by introducing race-dependent payoff functions. First, a lower matching threshold for minority-fintech matches generates a relatively larger share of minority borrowers using fintech lenders. Second, the race-dependent utility component results in a difference in the minority-non-minority rating gap for borrowers matched with fintech lenders than with banks.

Racial Disparities in Previous Lending Relationships. Now, we allow for racial disparities in previous lending relationships but assume race-independent matching values (payoff functions). The parameter assumptions are,

(1) The fraction of borrowers who possess previous lending relationships is α^m for minority borrowers and α^n for non-minority borrowers.

(2) The payoff function is race neutral. That is $p_{i,j}(\gamma_i,\theta_{i,j})=\ \gamma_i$ for both minority and non-minority borrowers matched with banks, and $p_{i,j}(\gamma_i,\theta_{i,j})=\ \gamma_i+\theta\gamma_i$ for both minority and non-minority borrowers matched with fintech lenders.

We have an equilibrium similar to the benchmark case where the matching threshold $\underline{\gamma}'$ and the fraction of matched borrowers among those with previous lending relationships ω' are determined by the following equations,

$$(1-\alpha^m)\,M^m\int_{\underline{\gamma}'(1+\theta)}^{\infty}f\left(x,\mu^m,\sigma^m\right)dx+(1-\alpha^n)\,M^n\int_{\underline{\gamma}'(1+\theta)}^{\infty}f\left(x,\mu^n,\sigma^n\right)dx=M^f$$

$$\omega'(\alpha^mM^m{+}\alpha^nM^n){+}(1-\alpha^m)\,M^m\int_{\underline{\gamma}'}^{\underline{\gamma}'\ (1+\theta)}f\left(x,\mu^m,\sigma^m\right)dx{+}(1-\alpha^n)\,M^n\int_{\underline{\gamma}'}^{\underline{\gamma}'(1+\theta)}f\left(x,\mu^n,\sigma^n\right)dx=M^b$$

Where $f(\mu^m,\sigma^m)$ and $f(\mu^n,\sigma^n)$ are the density functions of the rating distribution for the minority and non-minority borrowers respectively.

The model's first prediction regarding the share of borrowers using fintech lenders relative to banks is directly affected by the assumption on lending relationships. If a smaller mass of minority borrowers have lending relationships than non-minority borrowers ($\alpha^m < \alpha^n$), we have a relatively larger share of minority borrowers use fintech lenders in equilibrium. On the other hand, the second prediction of no difference in the minority-non-minority rating gap between fintech lenders and banks remains the same as in the benchmark case. This is because the payoff function is also race-neutral in this case.

Discussions. An important challenge to conducting empirical analyses of the first channel is that matching values are empirically unobserved. A key prediction of our model is that we can empirically test whether the matching values are race-dependent using the difference in the minority-non-minority rating gap between fintech lenders and banks. Moreover, both borrower and lender side factors can affect the race-dependent matching values. Investigating the relationships between the fintech-minority rating gap and such factors can be an additional way to test the race dependence of the matching values. On the borrower side, the race dependence of the preference for technology is likely to be smaller for borrowers with more soft assets. On the lender side, racial biases may be mitigated when lenders are more geographically focused.

As for the second channel on previous lending relationships, predictions of the model are empirically testable. We could directly test whether minority borrowers are less likely to have previous lending relationships and whether a racial difference in the share of borrowers with lending relationships is translated into racial disparities in fintech usage. In addition, structural estimation of the matching game can provide further insights into the relative importance of the two channels.

II. Data and Summary Statistics

A. Data Sources

Our analysis relies mainly on a linked database of loan-level information on restaurants in the Paycheck Protection Program (PPP) and the full history of customer ratings downloaded from Yelp.com. For the PPP dataset, we use the loan-level data release on March 2, 2021 (through sba.gov, FOIA), which is the most detailed and comprehensive version of loans of all sizes. The entire PPP dataset contains around 6.46 million loans processed by 5,593 lenders, among which around 0.37 million loans (5.77%) are for businesses in the Food Services and Drinking Places sector (NAICS code 722). We restrict to the first-draw recipients in 2020 and 2021, which refers to first-time loans applied for by borrowers in 2020 and 2021.

The key information we use from the PPP data includes the business name, address, state, zip code, industry, business entity type, reported employment size, and franchise name for borrowers; and the formal organization name, address, city, state, and zip code for lenders. We restrict our loan sample to only first draws in order to better capture the matching between borrowers and lenders. The completeness of the 2021-March release of the PPP data enables us to address questions that have not been answered in previous studies,[11] and is crucial for our study because minority-led businesses tend to be smaller (Fairlie and Robb (2008), Tareque et al. (2021))) and received a smaller loan (Atkins et al. (2021), Fairlie and Fossen (2021a)).

First and foremost, to carry out our analysis we need to distinguish between traditional and fintech lenders, for which we mainly rely on the FinTech Company List published on the SBA official website (sba.gov). We supplement the official FinTech Company List with information from the SBA state subsidiaries' websites and major news sources. We identify 15 fintech lenders and the full list is in Table A2 in the Appendix.[12] We present the comparison between our sample and the Erel and Liebersohn (2020) sample in the Online Appendix B-Table B1, which further confirms the reliability of our classification. We do not classify all non-banks as fintech lenders because one crucial feature of SBA lending programs is the participation of many traditional non-bank lenders, such as CRF Small Business Loan Company, LLC and Hana Small Business Lending, Inc., as means to facilitate the funding needs of less bank-connected small businesses. Regarding the lending technology, these non-banks are similar to banks.[13] Details on the construction of the sample of fintech lenders are stated

[11] Other papers studying the Paycheck Protection Program (Erel and Liebersohn (2020), Granja et al. (2020), Li and Strahan (2021)) use the early release of the PPP data that contains borrower names only for loans above $150,000. The full release used in our paper contains borrower-level identifiable information for loans both above and below $150,000, which enables us to link with Yelp rating data for the full sample.

[12] Appendix-Table A2 also reports the percentage of loans that are included in our final sample linked with Yelp ratings, which indicates that our linked sample is evenly distributed across each fintech lender.

[13] Other papers on small business lending (Gopal and Schnabl (2020)) and the mortgage credit market (Buchak et al. (2018), Fuster et al. (2019)) also make the distinction between fintech companies and other

in the Online Appendix C1.

Second, we need to identify minority-owned businesses among PPP loan recipients for a representative sample. One limitation of the PPP loan-level data is that the information on the race and ethnicity of loan recipients is missing for almost 80% of the sample and may have selection biases in the sample that has the demographic information. To address this challenge, we restrict to a sample of restaurants among the PPP recipients for which we find a match on yelp.com and use the food type information as a proxy for the race and ethnicity information of the restaurant owners. We classify restaurants into four groups: African American, Asian (including Pacific Islander), Hispanic, and White.[14] We cross validate our measure of minority-owned business by comparing the Yelp racial group variables and the PPP racial group variables and results are reported in Appendix Table A3. Our proxy provides a conservative measure given that the false positive rate is reasonably low. [15]

Third, we use the customer ratings from yelp.com to gauge the minority-non-minority gap between fintech and non-fintech borrowers. Yelp ratings are used as a proxy for operational performance (Bernstein and Sheen (2016), Huang (2020), Lynch (2021)) and shown to be related to revenue increase (Luca (2016)).[16] We collect the full history of the ratings and construct a restaurant-month panel by taking the average of ratings in each month for each restaurant. Using a panel of the ratings has the benefits of the possibility of controlling for time trends in ratings by including monthly fixed effects.

Lastly, we merge in other datasets to enrich the scope of our analysis, including other restaurant-level information from yelp.com, 7(a) and 504 program loan-level data from 1990 to 2019, and HUD USPS zip code crosswalk files. In addition, we classify lenders into banks, Certified Community Development Financial Institutions (CDFIs) loan funds/Certified De-

non-banks.

[14]Some examples are African, Somali, and Soul Food as African American; Asian Fusion, Japanese, Chinese, and Pakistani as Asian; Acai Bowls, Caribbean, and Mexican as Hispanic.

[15]The concurrent literature addresses the data incompleteness of demographic information by conducting zip-code/county level analysis (Erel and Liebersohn (2020), Fairlie and Fossen (2021a)), restricting to the subset of PPP recipients with demographic information (Atkins et al. (2021)), estimating the racial group based on borrower name and location (Howell et al. (2021))), and linking the PPP data with restaurant licenses and voter registrations in Florida (Chernenko and Scharfstein (2021)).

[16]There is recent literature discussing the effectiveness of customer ratings (Mayzlin et al. (2014)), and using the Yelp ratings as a measure of restaurant sales (Anderson and Magruder (2012)) and visits (Davis et al. (2019)), and investigating the informativeness of customer ratings in residential home services (Farronato et al. (2020)), physician choice (Xu et al. (2021)), and books on Amazon (Reimers and Waldfogel (2021)).

velopment Companies (CDCs), and other non-banks and match the PPP lenders with financial institutions on the Federal Financial Institutions Examination Council (FFIEC) list to have more detailed lender classifications. Details on the lender classification and steps to match with FFIEC are in Online Appendix C2.

Details on variable definitions and data sources can be found in Table A1 in the Appendix.

B. Sample Design

We construct a linked database by matching the borrowers in the PPP dataset to the restaurants on yelp.com. The PPP-Yelp linked dataset offers several advantages. First, it provides information on detailed borrower-level characteristics and a proxy for minority-owned businesses for a representative sample. Second, essentially all restaurants were eligible for PPP while the standard is higher in other industries. This rules out the possibility that our results are driven by sample selection bias due to eligibility.[17] Third, the restaurant industry is among the most Covid-19 vulnerable industries and thus provides a setting where the credit demand and borrower participation is high.

We use both code-based algorithms and manual corrections for the matching procedure. Details on the linking procedure are described in the Online Appendix C3. 104,293 loans are matched to a meaningful link on yelp.com, which account for 28.01% of the whole PPP sample in the Food Services and Drinking Places sector. The matching rate is reasonable given that our matching criteria are strict. For the empirical analysis, we further limit the sample to restaurants that have at least one rating record since April 2018. Online Appendix C3 also provides a comparison between the linked and unlinked samples which shows a high similarity between two.

C. Summary Statistics

We mainly use two datasets: one cross-sectional dataset that consolidates the various data sources described above and one restaurant-level panel dataset on historical customer rat-

[17]For example, if the eligibility is size-based, we would have a different sample of the minority-owned businesses than non-minority-owned businesses that are eligible for the PPP as the minority-owned businesses tend to be smaller.

ings. Our final cross-sectional dataset consists of 98,825 restaurant borrowers in the PPP that are active in business from April 2018 to March 2021. The observation level is a restaurant-lender-loan triplet. The loan and lender characteristics are observed at the PPP loan origination time; the restaurant characteristics are from yelp.com and are observed at the time of data collection (March 2021 to July 2021). The restaurant-level panel dataset provides the monthly average of rating stars for the 98,825 restaurants in our sample from April 2018 to March 2021.

[INSERT TABLE 1 AROUND HERE]

Table 1 shows the summary statistics of key variables in the cross-sectional dataset for the borrowers in the 2020 (Panel A) and 2021 (Panel B) waves, for both the full and the matched samples where the matched sample is constructed by matching minority borrowers with non-minority borrowers in the same state, business type group (aggregated), food price range, and of a similar size with a difference of at most five employees. The recipients in the 2021 wave appear to be different from the recipients in the 2020 wave in our sample. For example, 32% of the 2020 and 38% of the 2021 recipients are minorities; 9% in 2020 and 17% in 2021 use fintech lenders; The average borrower in 2020 (2021) has 18.62 (9.39) employees, and has a total number of 52.08 (33.01) customer reviews during the period from April 2018 to March 2021. Overall, the 2021 wave tends to contain a larger part of financially disadvantaged borrowers than the 2020 sample. When comparing the full and matched samples, we observe pattern that is consistent with the minority-owned businesses being in a disadvantaged location and business status.

Table 1 Panel (c) shows the summary statistics of rating stars in the panel dataset for the borrowers in the 2020 and 2021 waves. The ratings are quite similar for the full and matched sample but higher for the 2021 recipients.

III. Regression Analysis

In this section, we first provide graphic illustrations and regression results on racial disparities in fintech usage. Then, we test our model's predictions about the channels of the race-dependent matching value and previous lending relationships. We also conduct robustness tests and study whether we observe similar patterns for other lender classifications such as first-time bank participants and non-federally insured lenders and whether our results are driven by variation in approval dates.

A. Fintech Lenders in the PPP Program

We start with graphic illustrations in the usage rate of fintech versus traditional lenders in the PPP program for minority- and non-minority-owned restaurants.

[INSERT FIGURE 2 AROUND HERE]

Figure 2 shows the daily dollar value of loans processed by fintech lenders (Panel (a)) and non-fintech lenders (Panel (b)) for minority- and non-minority-owned restaurants in the 2020 PPP. Before the entry of major fintech lenders on April 10 2020 , there is an enormous gap between the dollar value of loans disbursed to minority- and non-minority-owned businesses. For example, on the first day, the dollar value of loans disbursed by traditional lenders to the minority-owned businesses is only 7.54% of the dollar value disbursed to the non-minority-owned businesses. In contrast, fintech lenders processed more than three million dollars of loans for minority borrowers on the first day of entry, about 35.96% of the dollar value disbursed to non-minority borrowers. In the second tranche that started on April 27, 2020, traditional lenders covered a relatively larger share of minority-owned businesses than in the first tranche, consistent with findings using the early data release of the subsample of larger loans (Fairlie and Fossen (2021a)). However, the gap between fintech and traditional lenders is still prominent, with the minority-non-minority ratio measured by dollar value being 53.38% for traditional lenders and 75.27% for fintech lenders.

Online Appendix A Figure A1 provides the figures on the 2021 PPP where we still observe a smaller minority-non-minority ratio for fintech lenders. We further decompose the minority-owned businesses into Black-, Asian-, and Hispanic-owned businesses and plot the daily disbursed dollar value by fintech and non-fintech lenders in the Online Appendix A Figure A2. The patterns look analogical across the three racial groups, especially after the entry of major fintech lenders.

[INSERT FIGURE 3 AROUND HERE]

Figure 3 plots the state-level minority shares separately for fintech loans and non-fintech loans. Figures 3(a) and 3(b) plot the minority share for fintech loans and figures 3(c) and 3(d) for non-fintech loans in 2020 and 2021, respectively. The cross-state variation in the minority shares for non-fintech loans are moderate. In contrast, we observe a larger dispersion across states in minority shares for fintech loans. These results suggest that fintech and non-fintech lenders play a different role in providing credit to minority-owned businesses.

B. Fintech Lenders and Minority Borrowers

In this subsection, we investigate whether minority-owned restaurants are more likely to use fintech lenders in the PPP program in a regression framework. We estimate the following specification:

$$I(\text{FinTech})_{i,c} = \beta I(\text{Minority Group})_i + \gamma X_i + \mu_c + \varepsilon_{i,c}$$

where the main dependent variable is a dummy variable equal to one if the restaurant owner i borrows from a fintech lender in the PPP program and 0 otherwise. The main independent variables, Black, Asian, and Hispanic, are dummy variables equal to one if the restaurant owner i is Black, Asian, or Hispanic respectively and 0 otherwise. The omitted category is other racial and ethnic groups, mainly composed of White-Americans.

To control for other borrower characteristics to the greatest extent given the available data, we include Employment for business size, $I(Franchise)$ for whether the business is a franchised brand, Business Type Dummies for different company organizational formats such as Corporation, L.L.C., Sole Proprietorship, and Self-Employment (Details in Appendix-Table A1). We include city fixed effects (μ_c) to control for time-invariant variation in local economic exposure to the Covid-19 shock and pre-pandemic conditions that might affect the propensity to get a fintech loan. Standard errors are clustered at the city level.

[INSERT TABLE 2 AROUND HERE]

Table 2 Panel A presents the results on the 2020 PPP. Column (1) shows that Black-, Asian-, and Hispanic-owned restaurants have a 9.17%, 8.44% and 1.22%, correspondingly, higher likelihood of using a fintech lender. The economic magnitude is large compared to the sample mean of fintech usage (9%). Coefficients are statistically significant at the 1% level for all groups. Through columns (2) to (4), we control for more characteristics and see how much of the positive association can be explained by observables. In column (2), we control for Employment Size which is shown as an important factor in banks' decision on borrower priority in the PPP (Balyuk et al. (2020), Humphries et al. (2020)) and is very likely to be correlated with minority ownerships. The coefficients before Black and Asian decrease by around 6% and the coefficient before Hispanic decreases by 11%. In column (3), we further control for I(Franchise) and Business Type Dummies, and the coefficients further decrease by around 6% for Black and Asian and by 17% for Hispanic.

When we control for city fixed effects in column (4) and thus compare the characteristics of business owners in the same city who borrow from different lenders, the coefficients before minority dummies decrease dramatically. The coefficient before Black decreases to 4.99%, which amounts to 32% of the correlation between Black ownership and fintech usage being explained by city fixed effects. Similarly, the coefficient before Asian decreases to 6.07%, amounting to 16% of the correlation explained by city fixed effects. The coefficient before Hispanic becomes negligible and statistically insignificant when controlling for city fixed effects. The large reduction in the economic magnitude and statistical significance of the coefficients when controlling for city fixed effects suggests that, to a large extent, the higher likelihood of using fintech lenders by minority-owned businesses is attributed to regional variation. This is consistent with the argument that historical roots such as "bank deserts" on the lender side (Erel and Liebersohn (2020), Wang and Zhang (2020)) and language and business capital weakness on the borrower side which is hard to eliminate in a short period of time are the sources of racial disparities in the credit market.

On the other side, consistent with Chernenko and Scharfstein (2021) and Howell et al. (2021), we still observe racial disparities after controlling for city fixed effects, suggesting non-geographic frictions, such as culture- and attitude-based racial bias plays, an important role in the outcome of PPP loan distribution being uneven for different racial groups. Results are robust when using the matched sample and are presented in columns (5) through (8).

Panel B presents the results of the 2021 wave. Like the 2020 wave, we observe that minority-owned businesses have a higher likelihood of using fintech lenders and the economic magnitude is close to the sample mean of fintech usage (17%). Cross-city variation plays an even larger role in the 2021 wave. Comparing columns (1), (3), and (4), city fixed effects explain 35% of the correlation between Asian and fintech usage. The coefficient before Black becomes insignificant and the coefficient before Hispanic decreases by 29%. The relatively larger part explained by city fixed effects in the 2021 wave suggests that the role of within-city variation in lender choices is reduced in the 2021 wave. This is consistent with that non-geographic-related race-dependent frictions in the lending process are reduced in the 2021 wave. Results are robust when using the matched sample, as reported in columns (5) through (8).

Taken together, Table 2 shows that minority-owned businesses are more likely to use fintech lenders in the PPP, even after controlling for borrower characteristics including employment size, franchise, and business type. While city fixed effects explain a large degree of racial disparities in terms of fintech usage, coefficients before the minority racial group dummies are still positive and significant after controlling for city fixed effects. This implies the existence of racial disparities in access to the credit market both across cities and within the same city.

C. Race Dependent Matching Values

We next explore the existence of racial-dependent frictions in the matching process. Motivated by our matching game model, we test whether minority-owned restaurants have a higher matching value with fintech lenders than with non-fintech lenders using the minority-non-minority gap in operational performance.

C.1. Minority-Non-Minority Rating Gap

We use Yelp rating as a proxy for operational performance and estimate the following specification:

$$\text{Rating}_{i,t} = \beta I(\text{FinTech})_i \times I(\text{Minority})_i + \delta I(\text{FinTech})_i + \delta I(\text{Minority})_i + \gamma X_i + \mu_{c,t} + \varepsilon_{i,c,t}$$

The dataset is a restaurant-month panel where the dependent variable is the monthly average of customer ratings for a given restaurant in the period from April 2020 to March 2021 (i.e., during the Covid crisis). The key independent variable is the interaction terms between the fintech indicator and the three minority racial group indicators. We also control for the fintech and racial group indicators themselves as well as borrower characteristics, which are all time-invariant variables. We account for within-restaurant correlation in errors by clustering all panel regressions by restaurants.

[INSERT TABLE 3 AROUND HERE]

Table 3 reports the results that compare the minority-non-minority rating gap between fintech and non-fintech borrowers. Columns (1) through (4) present the results for the 2020 wave, and columns (5) through (8) for the 2021 wave. In column (1), the rating gap between Black- and non-minority-owned restaurants is 0.25 stars (6.4% of the sample mean) more negative for fintech borrowers than for the traditional borrowers. Similarly, for Asian-owned restaurants, the rating gap between Asian- and non-minority-owned restaurants is 0.06 stars (1.5% of the sample mean) more negative for fintech borrowers than for the traditional borrowers. When controlling for city fixed effects in column (2), the coefficient before the interaction term with Black decreases by 8% and the one with Asian decreases by 33%. This decrease in magnitude after controlling for city-fixed effects is consistent with our findings regarding the correlation between minority ownership and fintech usage. Results of the Hispanic-owned restaurants are insignificant. Columns (3) and (4) report results using the matched sample which are consistent with the results of the full sample.

We observe different results in the 2021 wave. The coefficients before the interaction terms between the fintech and racial group indicators for Black- and Asian-owned restaurants become insignificant, yet for Hispanic-owned restaurants, we observe significant negative coefficients before the interaction terms. For example, column (5) shows that the rating gap between Hispanic- and non-minority-owned restaurants is 0.18 stars (or 4.6% of the sample mean) more negative for those who use fintech lenders than for those who use traditional lenders. One possible explanation for the difference between racial groups is that most of the Black and Asian borrowers in the blind zone of traditional lenders already participated in the PPP program in 2020, and thus the additional participants in the 2021 wave via fintech lenders are similar between minority and non-minority borrowers. Hispanics might lag in applying for the PPP through fintech lenders. A greater number of Hispanic borrowers neglected by traditional lenders applied for PPP loans via fintech lenders in 2021. Controlling for city fixed effects increases the racial gap, suggesting higher within-city variation in racial-dependent frictions in the borrower-lender matching process. Results are robust when using the matched sample.

We also report results using pre-Covid period ratings in Online Appendix B2 where we still observe a negative sign before the interaction between the Fintech dummy and the Asian dummy in the 2020 wave. Table B3 presents the results where we run regressions on separable subsamples of fintech and non-fintech borrowers. We find that the minority-non-minority rating gap is insignificant, or less negative, for traditional lenders, which is consistent with traditional lenders posing higher barriers for minority than non-minority borrowers.

Taken together, Table 3 shows that fintech lenders are more inclusive for minority borrowers in the sense that fintech lenders exert lower racial barriers. Consistent with the argument in Berger et al. (2021b) that an increase in convenience appears to be the very central reason for fintech lending growth, our findings suggest that the convenience nature of fintech lenders also makes the credit market more accessible to minority-owned businesses.

C.2. Lender Heterogeneity

We further explore heterogeneity among lenders by running the same regression specifications as in Table 3 but using a series of dummies, one for each lender. We focus on the four biggest fintech lenders: Cross River Bank, Kabbage, Square, and Paypal, and the seven largest banks:

JPMorgan, Bank of America, Wells Fargo, U.S. Bank, Truist, PNC, and TD Bank. We set the threshold of big lenders where each lender covers at least 1% of the observations in our restaurant-month panel dataset of ratings. [18]

[INSERT FIGURE 4 AROUND HERE]

Figure 4 shows the results for the largest minority group in our sample: Asian-owned restaurants. Consistent with the pooled-lender regression results, the Asian-non-minority gap in ratings is slightly positive for Cross River Bank and negative for the other fintech lenders in the 2020 wave, indicating lower user barriers for minority-owned businesses by fintech lenders. In contrast, banks tend to have positive racial barriers, especially for smaller banks. For the largest three banks, JPMorgan, Bank of America, and Wells Fargo, the rating gap is either small or not significantly different from zero, suggesting that big banks provide credit to a similar group of minority- and non-minority-owned restaurants in terms of rating levels. For relatively "small" big banks, the rating gap is positive and large. Given that big banks are likely to have better online lending platforms, this difference between large and small banks is consistent with the argument that the convenience of automated lending process reduces the racial barriers in small business lending.

In 2021, there is no clear difference between fintech lenders and banks. This aligns with our pooled-lender regressions and implies an improvement in 2021 that fintech and non-fintech lenders provide credit to a similar segment of minority- and non-minority-owned businesses. Online Appendix Figure A3 and Figure A4 present plots for the African Americans and Hispanics, respectively, where the patterns are also consistent with our results of the pooled-lender regressions.

C.3. Business Capital of Borrowers

Our model predicts that a larger difference in the preference for technology between the minority and non-minority borrowers will translate into a larger difference in the minority-non-minority rating gap between fintech and non-fintech lenders. We test this hypothesis

[18] Cross River Bank, JPMorgan, Bank of America, and Wells Fargo each cover about 2.20%, 4.74%, 6.96%, and 4.26% of the observations, and other lenders cover a share of 1%-2% of the observations per lender.

by studying whether the difference in the minority-non-minority rating gap between fintech and non-fintech lenders is smaller when the borrower has a higher level of business capital. Because business capital can provide more information about the restaurant, it can be soft assets that serve as a role of collateral (Hochberg et al. (2018), Davis et al. (2020)). As a result, the business capital of borrowers may be a way to mitigate the racial barriers in the small business lending market.

We use the total number of ratings during our entire analysis sample period from April 2018 to March 2021 as a proxy for business capital.[19] For two otherwise similar restaurants, the one with more reviews has more available information and can be seen as having a better reputation, and thus a higher level of business capital.

[INSERT TABLE 4 AROUND HERE]

Table 4 reports the results. The coefficients before the triple interaction between the fintech lender indicator, the minority borrower indicator, and business capital are positive and significant at the 1% level in all specifications for Asian- and Hispanic-owned restaurants in the 2020 wave. Columns (1) through (4) present the results for the 2020 wave. Column (1) shows that an increase of 100 reviews during our entire analysis sample period, which amounts to around one unit of sample deviation, is associated with a 0.07 star (or 1.17 times the original racial gap) smaller fintech-minority rating gap for the Asian recipients and 0.09 star (or 0.82 times the original racial gap) smaller for Hispanics. Column (2) controls for city-month fixed effects, columns (3) and (4) use the matched sample and the results are similar in magnitude.

Columns (5) through (8) present the results for the 2021 wave. Coefficients before the triple interaction terms are larger for Asian-owned restaurants, especially when controlling for city fixed effects. Coefficients before the triple interaction terms with Hispanic-owned restaurants become insignificant. We also report results using pre-Covid period ratings in Online Appendix B4 and the results are consistent.

Overall, we find that borrowers with higher levels of business capital experience lower

[19] Shi (2021) uses the firm size as a proxy for business capital to study how business capital increases the likelihood of being a PPP recipient.

racial barriers. This suggests that a racial gap in tech-preference on the borrower side contributes to the difference in the minority-non-minority rating gap between fintech and non-fintech lenders.

C.4. Geographic Scope of Lenders

Another prediction of our model is that the difference in the value of lending relationships between the minority and non-minority borrowers is also positively related to the minority-non-minority rating gap between fintech and non-fintech lenders. We test this hypothesis by investigating whether the difference in the minority-non-minority rating gap between fintech and non-fintech lenders is smaller for more geographically focused lenders. As the value of lending relationships tends to be formed and reinforced through interactions, more lender attention allocated to the region where the borrower is located can mitigate the racial gap. As a result, we observe a smaller racial gap for more geographically focused lenders.

We use the relative geographic lending scope (GS_r) as a proxy for the relative lender attention allocated to a given geographic region. GS_r is calculated as the total number of zip codes divided by the total number of cities that the lender covers in the entire PPP loan sample. For this part of the analysis, we drop CDFIs/CDCs as they may have specific regional requirements.

[INSERT TABLE 5 AROUND HERE]

Table 5 reports the results. Columns (1) through (4) present the results for the 2020 wave. Column (1) shows that an increase of one location of GS_r is associated with a 0.16 star (or 0.64 times the original racial gap) larger fintech-minority rating gap for the Black recipients and a 0.04 star (or 0.67 times the original racial gap) larger fintech-minority rating gap for the Asian recipients. Coefficients before the interaction terms with Hispanics are insignificant. Column (2) controls for city-month fixed effects, columns (3) and (4) use the matched sample and the results are similar in magnitude.

Columns (5) through (8) present the results for the 2021 wave. We observe insignificant results for Blacks and Asians but negative and significant results for Hispanics, which is in alignment with our main results in Table 3 on the racial gap. Results using pre-Covid period ratings are reported in Online Appendix B5 and are consistent. Online Appendix Table B6 presents results where we do the similar analysis but include both the geographic lending scope at the city level (GS_{city}) and at the zip-code level (GS_{zip}) where we find positive coefficients for the triple interaction with GS_{city} and negative coefficients for the triple interaction with GS_{zip}. This further confirms the importance of relative geographic focus.

Overall, we find that borrowers that are matched with more geographically focused lenders are associated with a lower level of racial gap. This is consistent with the existence of racial biases on the lender side.

D. Racial Disparities in Previous Lending Relationships

In this section, we study whether racial disparities in terms of previous lending relationships contribute to the variation in fintech usage among racial groups. It is possible that a smaller share of minority-owned restaurants have lending relationships, and therefore the minority-owned restaurants are relatively more affected by the crowding-out effects of restaurants with lending relationships. We test this hypothesis by comparing the share of borrowers with lending relationships for minority- and non-minority-owned restaurants.

[INSERT TABLE 6 AROUND HERE]

Table 6 reports the results. We measure previous lending relationships using a proxy that is a dummy variable equal to one if the borrower has at least one SBA 7(a) or 504 loan from 2009 to 2019. Panels A and B present the regression results on the relationship between the minority racial group dummies and lending relationship dummy for the 2020 and 2021 waves respectively. Results for the full sample are in Panel A columns (1) – (4). Column (1) shows that Black-, Asian-, and Hispanic-owned restaurants are 1.56% (52% of the sample mean), 1.57% (52% of the sample mean), and 1.64% (55% of the sample mean), less likely to have previous SBA lending relationships, respectively. In column (2), we control for employment, and the magnitude of coefficients before the minority racial groups decrease slightly.

In column (3), after controlling for a dummy for franchise and business entity type dummies, the magnitude of coefficients before the minority racial groups decrease by more than 35% and even become statistically insignificant for Black-owned restaurants. This implies that part of the reasons that minority-owned businesses are less likely to have previous lending relationships are due to their business type. In column (4), we control for city fixed effects and the magnitude of the coefficient before Asian-owned restaurants increases by 33.33%. In contrast, the magnitude of the coefficient before Hispanic-owned restaurants decreases by 6.67%. The difference between Asian- and Hispanic-owned restaurants in the aspect of within- versus across-city variation is in alignment with our findings in the fintech usage rate: within-city variation accounts for a large share of disparities for Asian-owned restaurants while across-city variation accounts more for the Hispanic group.

Columns (5) – (8) show the results for the matched sample where we find results that are similar but slightly smaller in magnitude for the Black and Asian groups and slightly larger for the Hispanic group. Coefficients before the minority racial groups become insignificant in most specifications in the 2021 wave, as reported in Panel B. This means that racial disparities in terms of lending relationships are also less severe among Black and Asian borrowers in the 2021 PPP yet more prominent among Hispanic borrowers. This finding is consistent with the evidence in section 4.3 that the 2020 and 2021 PPPs cover a different segment of borrowers.

Panels C and D report the results on how lending relationships are related to fintech usage in the 2020 and 2021 waves respectively. We find that restaurants without lending relationships are 5-7% (56% -78% of the sample mean) more likely to use fintech lenders in 2020 and 10%-18% (59% -106% of the sample mean) more likely to use fintech lenders in 2021, using specifications with different control variables. Interestingly, after controlling for lending relationships, compared with the results in Table 2, the coefficients before the minority racial groups only decrease slightly (4 -7 basis points) in the 2020 wave and even increase in the 2021 wave in some specifications. This finding is consistent with the findings in Howell et. al. (2021) that minority borrowers are more likely to use fintech lenders even controlling for previous lending relationships.

Results using a measure of previous lending relationships based on the dollar value of

7(a) and 504 loans are similar and are reported in Online Appendix Table B7.

Taken together, our findings support that the share of borrowers with lending relationships leads to a difference in the fintech usage rate. We find that minority borrowers have a lower level of previous lending relationships in the SBA programs, and borrowers without lending relationships are more likely to substitute traditional lenders with fintech lenders. Yet, it is also worth noticing that lending relationships cannot fully explain the racial disparities in the borrower's choice between fintech and non-fintech lenders.

E. Other Lender Types

In this section, we study other types of lenders, including first-time banks, non-federally-insured lenders, credit unions, community development financial institutions and community development corporations, and savings loan associations, to see if non-technology-related features of fintech lenders coincidentally lead to our main empirical findings.

E.1. First-Time Bank Participants

It is possible that fintech lenders are new entrants to SBA programs and therefore attract a different segment of borrowers. We test this hypothesis by studying the 672 first-time participants out of the 4,131 PPP bank sample, which accounts for around 4.04% of the loans.

[INSERT TABLE 7 AROUND HERE]

Table 7 reports the results. Panel A shows that the relationship between minority borrowers and the likelihood of being matched with newly entered banks is significantly lower for Asian-owned restaurants and insignificant for Black- and Hispanic-owned restaurants. Moreover, Panel B shows that the minority-non-minority rating gap is insignificant or more positive for fintech lenders compared with non-fintech lenders. The results indicate that, unlike fintech lenders, if anything, first-time banks attract a segment of higher-rated minority-owned restaurants than non-minority-owned restaurants. Our results suggest that the mitigating role of fintech lenders for racial-dependent frictions in the borrower-lender matching process is unlikely to be due to the new entrant nature of fintech lenders.

E.2. Non-Federally-Insured Lenders

Our racial disparity results might also be driven by regulatory differences in federally-insured and non-federally-insured lenders, given the large overlap between fintech lenders and shadow banks (Buchak et al, 2018). In the PPP, all federally insured depository institutions, credit unions, and Farm Credit System institutions are eligible to participate directly. For non-insured lenders, as most fintech lenders are, they need to apply for approval to be enrolled in the program.[20] We use the FFEIC data to identify whether the lender is federally insured or not. There are 11 non-federally-insured lenders out of the 3,658 FFEIC lender sample, which accounts for around 0.58% of the loans.

[INSERT TABLE 8 AROUND HERE]

Table 8 reports the results. Panel A shows that Asian-owned restaurants are more likely to use non-federally insured lenders but the effect becomes less significant or insignificant after controlling for city fixed effects. Results for Black-owned restaurants are positive in the 2020 PPP but negative in the 2021 PPP. Results for Hispanic-owned restaurants are insignificant. Panel B shows the results on the rating gap where we find insignificant results for most of the coefficients before the interaction terms between minority racial groups and lender type dummies and significant and positive results for Hispanic-owned restaurants.

Taken together, we do not find similar results on the lender usage and rating gap based on the contrast between federally insured and non-federally insured lenders. This suggests that it is unlikely that fintech lenders are more inclusive for minority borrowers because of their non-federally insured nature.

E.3. Others

We also investigate other lender classifications, including credit unions, community development financial institutions and community development corporations, and savings loan

[20].https://home.treasury.gov/system/files/136/PPP%20Lender%20Information%20Fact%20Sheet.pdf

associations. Results are reported in Online Appendix Table B7-B10.

Credit unions are the second-largest type of bank alternatives among PPP lenders, composing 409 out of the 3,658 lenders that we find a match with FFEIC, accounting for 3.48% of the loans. If our documented minority-non-minority gap is because of the unobserved characteristic of borrowers that prefer lenders offering more attractive loan terms, (and not due to racial barriers), we should observe a similar pattern for the comparison between credit unions and banks as for the comparison between fintech lenders and banks. However, we observe the same signs of the coefficients of the credit union usage likelihood and the rating gap, which suggests that the segment of minority borrowers served by credit unions are those who have a better evaluation with banks, rather than those who are more undervalued. We do not find the same results for credit unions as for fintech lenders.

In addition, we investigate whether fintech lenders mimic the role of community development financial institutions (CDFIs) and community development corporations (CDCs). There are 54 CDFIs/CDCs in the sample of 4,185 lenders, accounting for 0.72% of the loans. At first glance, CDFIs and CDCs play a similar role as fintech lenders as we find that minorities are more likely to use CDFIs/CDCs in the 2020 wave. However, results become insignificant and even significantly negative for Asian-owned restaurants in the 2021 wave. Moreover, we find no significant results on the rating gap. Our findings imply that while CDFIs and CDCs are able to cover more minority-owned businesses, they play a limited supplemental role in extending credits to minority-owned businesses that are more undervalued by traditional lenders.

Finally, fintech lenders are also well-known as an alternative option of mortgages and might be more familiar to lower-rated minority-owned businesses. To address this possibility, we study 25 savings loan associations (SLs) that mainly offer affordable mortgages as a comparison group to banks. However, we do not find similar patterns for SLs as for fintech lenders. If anything, we find a negative association between minority borrowers and SLs usage and a more positive difference in the minority-non-minority rating gap between fintech and non-fintech lenders.

F. *Loan Approval Speed*

Another alternative explanation of the racial disparities in fintech usage is a difference among borrowers in the preference of loan processing speed. The existing literature documents that fintech lenders process mortgage applications much faster than other lenders (Fuster et al. (2019)). In addition, Online Appendix Table B13 shows that on average fintech lenders have a higher loan processing capacity. Therefore, it might be that a different group of minority and non-minority borrowers prefer quicker loan processing and turn to fintech lenders disproportionally more.

[INSERT TABLE 9 AROUND HERE]

Table 9 shows the regression results that compare the difference in the number of days needed to get the loan approved from the entry of fintech lenders in the 2020 PPP and the beginning of the 2021 PPP wave between the minority and non-minority borrowers matched with fintech and non-fintech lenders.[21] In the 2020 wave, the coefficients before the interaction terms between the racial group and fintech indicators are insignificant for the Black- and Hispanic-owned restaurants. For Asian-owned restaurants, the coefficients before the interaction terms between the racial group and fintech indicators are positive and significant at the 1% level. This is consistent with a higher barrier that minority borrowers face to access the traditional credit market and thus turn to fintech lenders later. Consistent with a reduction in racial barriers in the 2021 wave using the rating gap, there are also improvements in waiting time. The coefficients before the interaction terms between the racial group and fintech indicators become negative for Asian- (8.11 days shorter) and Hispanic-owned restaurants (8.72 days shorter). Results on Black-owned restaurants are insignificant.

In Online Appendix Table B12, we use the full sample of the 2020 PPP and limit the sample to the second tranche in the 2020 PPP. Results are robust. Online Appendix Table B13 reports results on the robustness check of Table 3 where we control for the approval date

[21]The measure based on approval dates is not the exact loan processing speed of the lenders. However, we do not have information on the application dates, and the measure using approval dates provides information on borrowers' preference for loan processing speed given that all the loan application starting dates are the same for all lenders.

fixed effects. This estimates the rating gap for loans approved on the same day, and thus rules out differences due to the borrower's position in the PPP application queue. Coefficients before the interaction terms between the racial group and fintech indicators are very close to those reported in Table 3, which implies that the racial disparities that we demonstrate do not come from a difference in loans approved earlier or later.

Overall, our findings suggest that minority borrowers turned to fintech lenders in the PPP program not because they have a higher preference for getting the loan earlier. In fact, our results show that minority borrowers who applied for a loan through fintech lenders had a longer waiting time in the 2020 wave than through non-fintech lenders.

IV. Semiparametric Matching Model

In this section, we employ a more structured approach to describe the matching equilibrium by using the semiparametric matching estimator developed by Fox (2018). The empirical matching model provides estimation on the relative importance of different channels, whereas the regression approach only describes correlations in the data.

The computational costs of estimating the Fox (2018) model increase rapidly with the number of parameters, and therefore, we only include covariates that are closely related to the borrower-lender matching process. To account for relationship persistence, we include an indicator for previous lending relationships between the borrower and the lender. The other covariate of interest in the match value function is the interaction term between the fintech lender indicator and the minority borrower indicator which captures the residual value generated by fintech-minority matches. Geographic distance is shown to be important by previous studies and we also include a covariate on the distance between the borrower and the lender, setting to zero when matching with a fintech lender. Finally, speaking to the rating-based sorting, we include an interaction term between the fintech lender indicator and the borrower's rating.

The empirical matching model is based on the assumption of *Revealed Preference* that more valuable matches are more likely to occur in the data. For instance, a positive coefficient on the product between the fintech lender indicator and the minority borrower indicator means that more value is generated by matching fintech lenders with minority borrowers, controlling for other variables, whereas a negative coefficient means that more value is generated by matching fintech lenders with non-minority borrowers. In other words, the coefficient before the product between the fintech lender indicator and the minority borrower indicator in the structural estimation of the matching game model provides the estimation of the relative importance of the fintech-minority matching value channel versus the lending relationship channel in the matching process.

A. Probit Model on the Matching Probability

Given the sample size and a large number of potential matches, it is computationally unfeasible to estimate the matching game model using the Fox (2018) approach on the full sample. In this subsection, we provide results on the full sample using the Probit model, which estimates how the characteristics of the borrowers and lenders contribute to the matching probability. Like the structural estimation using the Fox (2018) approach, this sheds light on the relative importance of different channels. Unlike the Fox (2018) estimator, the Probit model estimates the matching probability without considering the interactions between different borrowers and between different lenders.

One important step in estimating a matching model is assignments of counterfactual matches. In addition to the matches observed in the data, we also need to know what are potential matches not happen in the dataset but are feasible in reality. Then, with the assumption that observed matches are more likely to occur than the potential unobserved matches, we can estimate how borrower and lender characteristics contribute to the matching probability. In the context of the PPP, we assume borrowers can borrow from any lenders who are active in the same city. That is, we identify feasible lenders as those who lend loans in the same city of the borrower according to the entire PPP dataset. Potential matches are generated by assigning each borrower with all feasible lenders of the given borrower.

If we observe a loan between the borrower and the lender in the PPP, the dependent variable of the Probit model equals one and zero otherwise. To be comparable with the structural estimation, we include the same key independent variables as described above. In addition to the interaction terms, we also include the variables themselves and the borrower size and the number of loans issued by the lender in the PPP as controls for the matching probability for the group of borrowers or lenders per se.

[INSERT TABLE 10 AROUND HERE]

Table 10 reports the regression results for the 2020 sample (Panel A) and the 2021 sample (Panel B). In both years, consistent with the literature, the coefficient before the lending relationship indicator is positive, and the coefficient before the geographic distance is negative. Notably, we observe positive coefficients before the interaction terms between the fintech lender indicator and the minority borrower indicator and are statistically significant at the level of 1%. This supports our hypothesis that minority borrowers have a higher matching value when matched with fintech lenders than with banks. The magnitude is similar in both years, with the channel of lending relationships being eight to nine times more important than the channel of fintech-minority matching values. Consistent with the patterns in Table 3, we have positive sorting between ratings and fintech usage in 2020 and negative sorting in 2021, as shown by the coefficients before the interaction term between the fintech lender indicator and the borrower's rating.

B. *Structural Estimation of the Matching Model*

The estimator developed by Fox (2018) is a maximum score estimator (Manski (1975)) which differs from other estimators in two ways. First, it takes into account the interactions between different players in the matching game, as opposed to a direct estimation of the probability using Probit or Logit models. Second, it does not require data on the transfer payments between the borrower and the lender which is unavailable in our setting. It is also more realistic to consider the utility related to race-dependent frictions and lending relationships as non-pecuniary. Data such as the interest rate a borrower would pay if it borrowed from a different lender from the one in the sample can be a candidate for transferred payments. Akkus et al. (2016) develops an estimator based on Fox (2018) when such data is observed. Models of differentiated product demand (e.g. Berry et al. (2004) also requires such information.

Chen and Song (2013) and Schwert (2018) are examples of empirical implementation of the Fox (2018) estimator in the borrower-lender matching game, without studying the mitigating role of fintech lenders in racial barriers. See Schwert (2018) for a detailed illustration of the estimator as well as identifying assumptions.

Without data on the transfer payments, a scale normalization on the parameter vector is needed. In other words, identification is only up to arbitrary order-preserving transformations of the parameters (Manski (1975)). We pick the normalization that the coefficient on the geographic distance covariate is fixed at -1. The negative sign is chosen based on findings in prior literature that borrowers and lenders that are located closer are more likely to match.

One important condition for the Fox (2018) estimator to be consistent is that the model uses all possible matches within the existing loan market. In other words, the model does not consider counterfactual cases in which borrowers choose lenders that are not available in the sample. This is a realistic assumption in our setting. However, one implication of this condition is that as each borrower and lender appear on both sides of inequality in the equilibrium condition (equation (1)), any individual characteristics cancel out. Only characteristics of the matched pair that are related to both borrowers and lenders enter the value function in the estimation. Therefore, we include products of the demeaned borrower and lender characteristics (Chen and Song (2013), Akkus et al. (2016), Schwert (2018)). By demeaning the variables on borrower and lender characteristics, we can interpret their interactions as covariance. For variables regarding both the lender and borrower sides, we include the original variable.

We parameterize the matching value as a linear function, $V(b,l) = X'_{b,l}\beta + \epsilon_{b,l}$, where $X_{b,l}$ includes characteristics of the matched borrower and lender pair. The objective function is a sum of indicators for satisfaction of the pairwise value comparison (inequalities in the terminology in Fox (2018):

$$Q(\beta) = \Sigma_{n=1}^{N}\Sigma_{(b_1,l_1),(b_2,l_3)\in\mu_n} 1\left[X'_{b_1,l_1}\beta + X'_{b_2,l_2}\beta \geq X'_{b_1,l_2}\beta + X'_{b_2,l_1}\beta\right] \tag{2}$$

The observed matches and potential matches are constructed in the same way as in the

Probit model in the previous subsection. That is, we identify lenders who lend at least one loan in the same city of the borrower as the borrower's potential lender set. Inequalities are generated by exchanging the matched lender in the observed data of a pair of borrowers, with the restriction that the exchanged lender is in each borrower's potential lender set. We use the differential evolution algorithm to optimize this maximum score estimator as the objective function is a step function and a global optimizer is needed.[22]

[INSERT TABLE 11 AROUND HERE]

Table 11 reports estimates of the matching model. Due to computational limitation, we restrict to the sample of the New York state that contains 9,372,434 inequalities for the 2020 sample and 101,686 inequalities for the 2021 sample. Results are consistent with the results of the regression analysis and the Probit model. The positive coefficient on the interaction of the fintech lender and minority borrower indicators means that more value is generated by matching fintech lenders with minority borrowers. The positive coefficient before the lending relationship indicator is consistent with that previous lending relationships between borrowers and lenders contribute positively to matching values. Comparing the two coefficients gives us the relative importance of the two channels in the matching process. We find that the "lending relationship channel" is 1.45 times as important as the 'fintech-minority matching channel" in the 2020 PPP and 2.05 times important in the 2021 PPP.

V. Conclusion

We provide novel evidence on the existence of racial disparities in the borrower-lender matching process that are related to fintech usage. Using the Paycheck Protection Program as a laboratory and a linked dataset on the PPP loans and restaurants on yelp.com, we find that minority borrowers have a higher matching value when matched with fintech lenders. Moreover, we also find that previous lending relationships are another important channel of racial disparities in the borrower-lender matching process, and is also related to fintech usage. The

[22] We use the Python differential evolution package in scipy. The package has randomness in the initialization step.

evidence suggests that minority borrowers face higher barriers than non-minority borrowers when using traditional lenders and fintech lenders can at least partially address this issue.

It is important to distinguish between different sources of racial disparities in small business lending because they have different policy implications. The "fintech-minority matching value channel" calls for greater attention to equitable credit access and reducing barriers in the lending procedure. The "lending relationship channel" asks for alleviating the negative impact of lending relationships on minority borrowers' access to the credit market and building relationships for minority borrowers.

With regard to external validity, this paper uses a national-wide sample of restaurants. The large geographic range of the sample mitigates concerns about biases due to the sample selection. On the one hand, the Food Services and Drinking Places sector has a similar degree of racial diversity as to the average of all industries according to the U.S. Bureau of Labor Statistics. For other sectors with a lower (higher) level of racial diversity, we would expect higher (lower) values of fintech lenders in lowering down the racial barriers. A lower degree of racial diversity would result in less information available on the minority businesses as well as smaller positive spillover effects among minority borrowers in the sector. On the other hand, restaurants are likely to have lower levels of collateral and assets and thus the lending relationship channel plays a more important role for them.

Whether governments should extend credit access to the minority-owned businesses underserved by traditional lenders is a normative question. On one hand, these minority-owned businesses are of lower rating levels. On the other hand, they are part of the fabric of their communities, employing local residents and supporting civic causes. Moreover, the existing literature finds that SBA loans have positive effects on firm growth and productivity (Krishnan et al. (2015); Brown and Earle (2017)), which implies that the lower operational performance of these minority-owned businesses may exactly due to being previously excluded from government loan programs.

This paper studies the first large-scale government loan program where major fintech lending platforms, such as Paypal, Kabbage, and Funding Circle, are allowed to be eligible lenders. Our study has important policy implications that speak to the debate on whether to allow for the participation of fintech lenders in fully or partially guaranteed government loan programs. Our findings suggest that there are systematic biases and blind spots in the traditional loan distribution channel and that can be covered by fintech lenders. This has implications beyond the Covid-19 period. Whether the credit access provided by fintech lenders improves the financial and operational performance of those underserved borrowers is an interesting topic for future research. In addition, the impact of the introduction of fintech lenders on traditional lenders is also a promising avenue for future research.

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Figures

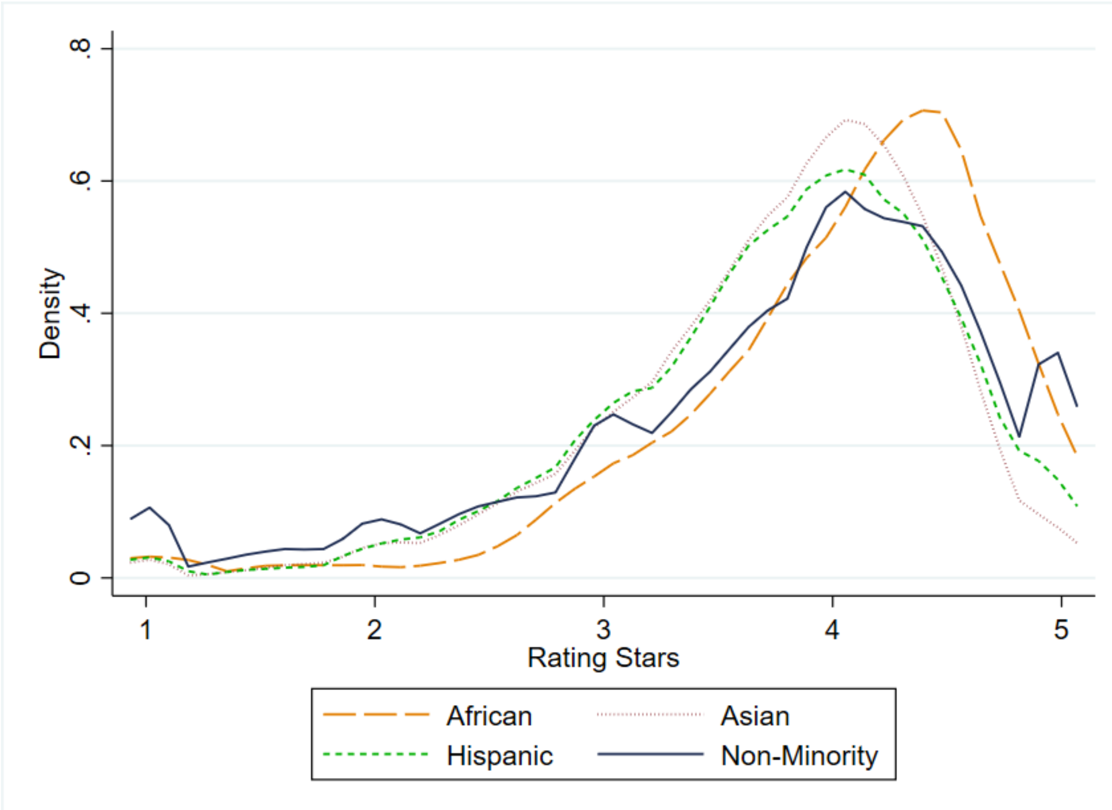
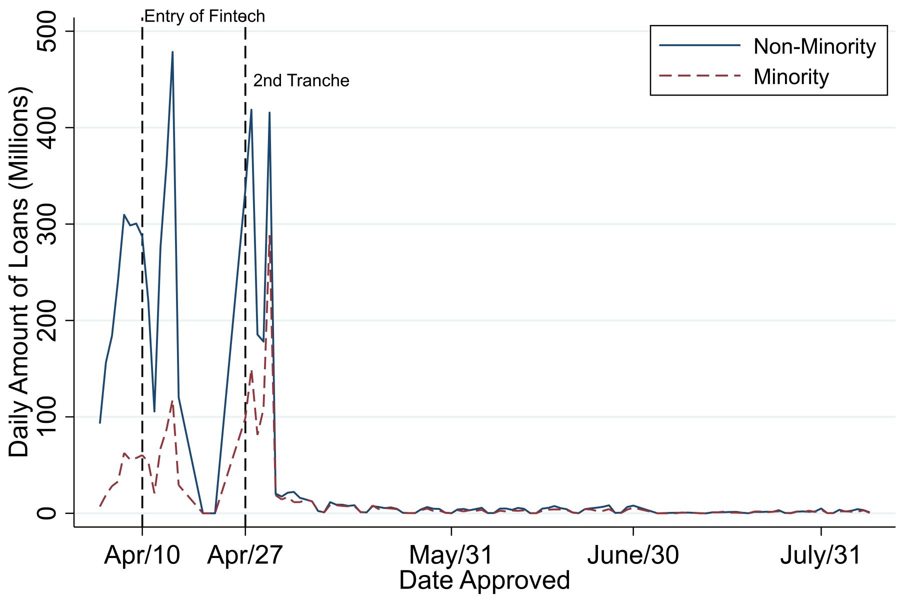
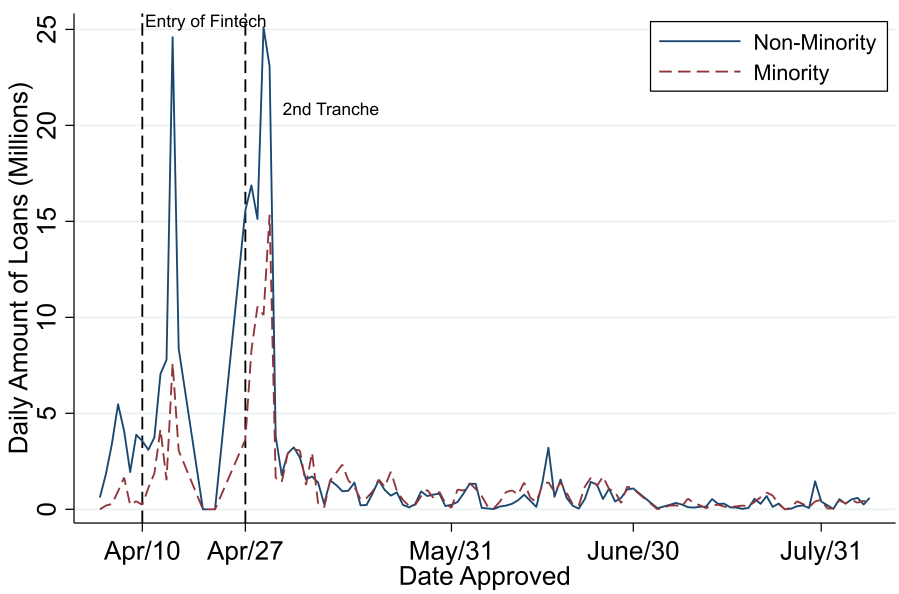


Figure 1: Distribution of Restaurant Ratings across Borrower Racial Groups

This figure plots the density of restaurant ratings for each racial group using data on customer ratings from yelp.com. For each restaurant in our linked sample, we calculate the mean of the monthly average of ratings from April 2018 to March 2021.



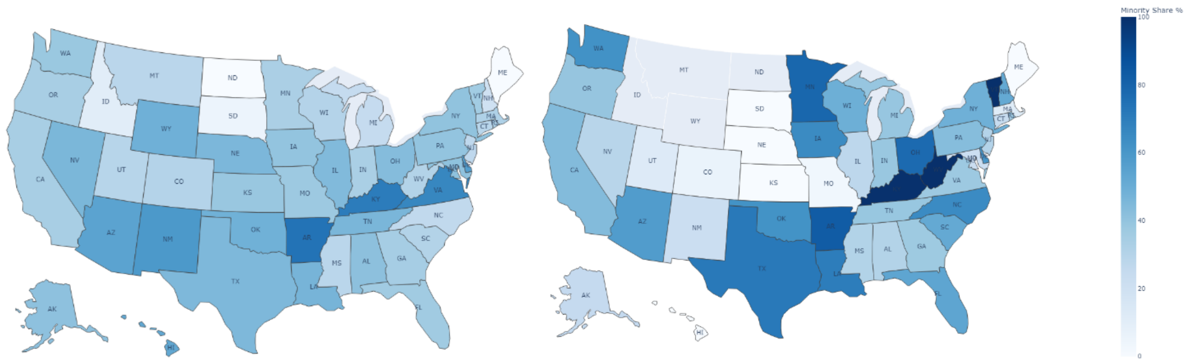
(a) 2020 PPP, Non-Fintech Lenders



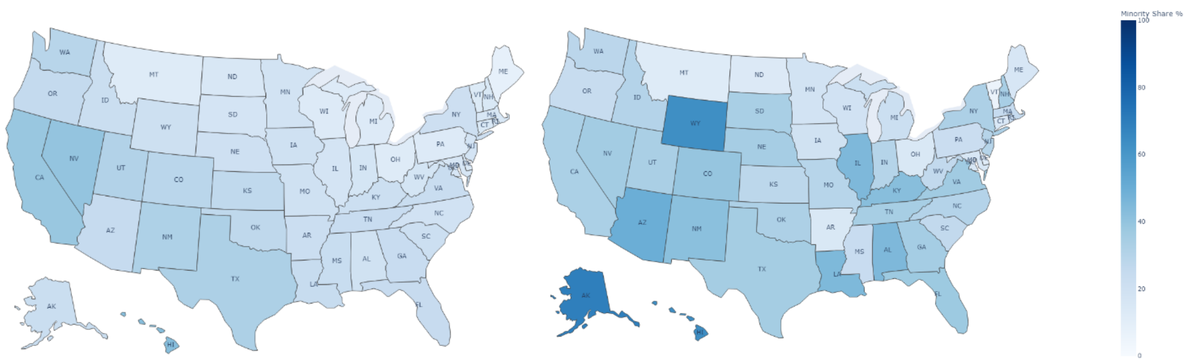
(b) 2020 PPP, Fintech Lenders

Figure 2: Minority- and Non-Minority-owned Businesses in the 2020 PPP Fintech vs. Non-Fintech (Dollar Value)

This figure plots the daily dollar value of PPP loans received by minority- and non-minority-owned restaurants that are processed by non-fintech (Panel (a)) and fintech (Panel (b)) lenders in the 2020 PPP wave for our sample. The 2020 wave spans the period from April 3, 2020 to August 8, 2020. The y-axis represents the daily dollar value of loans processed (in USD millions), and the x-axis represents the loan approval date. The blue solid line plots the non-minority-owned restaurants and the red dashed line plots the minority-owned restaurants. The first vertical dashed line indicates the entry of fintech lenders on April 10, 2020 and the second vertical dashed line indicates the beginning of the second tranche of the 2020 PPP on April 27, 2020.



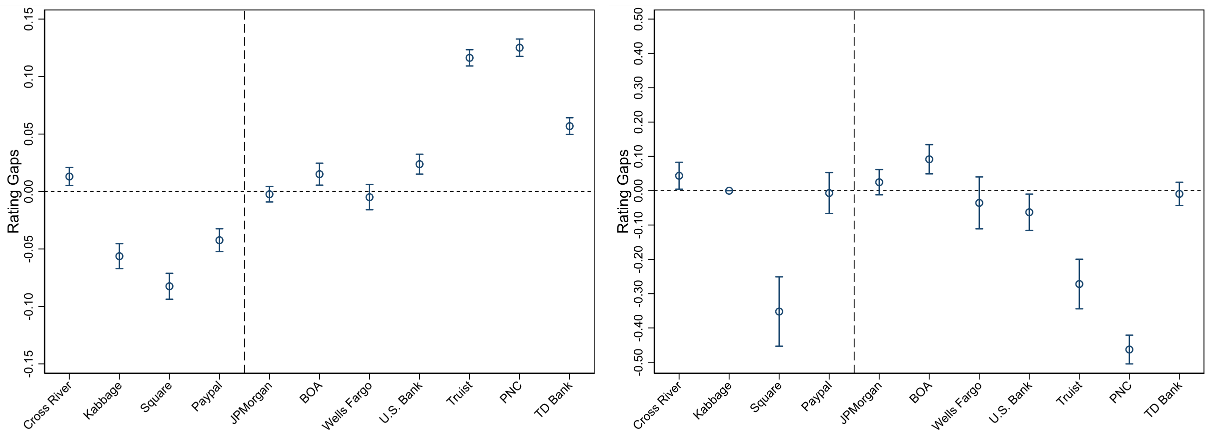
(a) Fintech in the 2020 PPP **(b)** Fintech in the 2021 PPP



(c) Non-Fintech in the 2020 PPP **(d)** Non-Fintech in the 2021 PPP

Figure 3: Percentage of Loans Distributed to Minority-owned Businesses Fintech vs. Non-Fintech (Dollar Value)

This figure plots the share of loan dollar value distributed to minority-owned businesses processed by fintech (Panels (a) and (b)) and non-fintech (Panels (c) and (d)) lenders in the 2020 and 2021 waves, based on our sample. The Minority Shares range from 0% (the lightest blue) to 100



(a) 2020 PPP Recipients

(b) 2021 PPP Recipients

Figure 4: Minority-Non-Minority Rating Gap (Asian-owned) Fintech vs. Non-Fintech

This figure plots the minority-non-minority rating gap for Asian-owned restaurants in the 2020 wave (Panel (a)) and in the 2021 wave (Panel (b)), using ratings from April 2020 to March 2021 (during the Covid crisis). The y-axis represents the coefficients before the interaction terms between the racial group indicator and lender indicators from the regressions as in Table 3, except that we decompose the fintech indicator into several dummies for each big fintech lender and bank. The x-axis represents each lender. We plot the biggest four fintech lenders in our sample: Cross River Bank, Kabbage, Square, and Paypal, and the largest seven banks in our sample: JPMorgan, Bank of America, Wells Fargo, U.S. Bank, Truist, PNC, and TD Bank. In each regression, the dependent variable is the Rating Stars, which range from 0 to 5, based on customer ratings from yelp.com. The Asian indicator is defined to be 1 for restaurants that we identify as Asian food restaurants. The $Lender_j$ (e,g., Kabbage) indicator is defined to be 1 for loans backed by that lender (e.g. by Kabbage). The omitted category is all other lenders. Control variables are the same as in Table 3 which contain lender dummies, racial group dummy, employment size, franchise dummy, month-city fixed effects, business type fixed effects, and eating policy dummies. Detailed variable definitions are in Appendix Table A1. Standard errors are clustered at the restaurant-lender level.

Table 1: Summary Statistics

(a) Panel A: Restaurant and Lender Characteristics – Cross Section 2020 PPP First Draw

	Full Sample								Matched Sample							
	N	Mean	S.D.	Min	P.25	Median	P.75	Max	N	Mean	S.D.	Min	P.25	Median	P.75	Max
I(Minority)	92557	0.32	0.46	0	0	0	1	1	86097	0.33	0.47	0	0	0	1	1
I(African Ame.)	92557	0.01	0.08	0	0	0	0	1	86097	0.01	0.08	0	0	0	0	1
I(Asian)	92557	0.18	0.39	0	0	0	0	1	86097	0.2	0.4	0	0	0	0	1
I(Hispanic)	92557	0.13	0.33	0	0	0	0	1	86097	0.13	0.34	0	0	0	0	1
Employment	92557	18.62	31.02	1	5	11	21	500	86097	14.79	17.44	1	5	10	19	500
I(Franchise)	92557	0.12	0.33	0	0	0	0	1	86097	0.11	0.32	0	0	0	0	1
I(Fintech)	92557	0.09	0.29	0	0	0	0	1	86097	0.1	0.29	0	0	0	0	1
δ(Date)	92557	26.87	24.19	0	10	25	28	127	86097	27.64	24.43	0	11	25	28	127
I(Relationships)	92557	0.03	0.18	0	0	0	0	1	86097	0.03	0.18	0	0	0	0	1
Rel. (N. Loans)	92557	0.04	0.25	0	0	0	0	8	86097	0.04	0.25	0	0	0	0	8
Rel. (A. Loan)	92557	18	3,074	0	0	0	0	680,000	86097	20	3,187	0	0	0	0	680,000
BC	92557	52.08	96.02	1	8	23	59	3,655	86097	50.98	91.22	1	8	23	58	3,655
GS_{zip}	92557	4,236	5,079	1	220	1,295	8,979	16,637	86097	4,362	5,140	1	225	1,354	10,684	16,637
GS_{city}	92557	2,715	3,252	1	159	835	6,096	11,415	86097	2,797	3,294	1	162	886	6,458	11,415
I(New Bank)	82,287	0.04	0.2	0	0	0	0	1	76,082	0.04	0.2	0	0	0	0	1
I(CU)	85,351	0.03	0.18	0	0	0	0	1	79,147	0.03	0.18	0	0	0	0	1
I(CD)	82,821	0.01	0.08	0	0	0	0	1	76,605	0.01	0.08	0	0	0	0	1

Table 1: continued

(b) Panel B: Restaurant and Lender Characteristics – Cross Section 2021 PPP First Draw

	Full Sample								Matched Sample							
	N	Mean	S.D.	Min	P.25	Median	P.75	Max	N	Mean	S.D.	Min	P.25	Median	P.75	Max
I(Minority)	6,268	0.38	0.49	0	0	0	1	1	6,024	0.39	0.49	0	0	0	1	1
I(African Ame.)	6,268	0.01	0.11	0	0	0	0	1	6,024	0.01	0.12	0	0	0	0	1
I(Asian)	6,268	0.22	0.41	0	0	0	0	1	6,024	0.22	0.42	0	0	0	0	1
I(Hispanic)	6,268	0.15	0.36	0	0	0	0	1	6,024	0.16	0.36	0	0	0	0	1
Employment	6,268	9.39	13.41	1	3	6	11	342	6,024	8.41	8.66	1	3	6	10	93
I(Franchise)	6,268	0.06	0.23	0	0	0	0	1	6,024	0.06	0.23	0	0	0	0	1
I(Fintech)	6,268	0.17	0.38	0	0	0	0	1	6,024	0.18	0.38	0	0	0	0	1
δ(Date)	6,268	41.12	21.14	0	23	39	60	78	6,024	41.01	21.05	0	23	39	60	78
I(Relationships)	6,268	0.02	0.13	0	0	0	0	1	6,024	0.02	0.13	0	0	0	0	1
Rel. (N. Loans)	6,268	0.02	0.16	0	0	0	0	3	6,024	0.02	0.15	0	0	0	0	3
Rel. (A. Loan)	6,268	0	0.06	0	0	0	0	3	6,024	0	0.06	0	0	0	0	3
BC	6,268	33.01	64.64	1	5	14	38	2,095	6,024	32.6	59.53	1	5	14	38	2,095
GSzip	6,268	5,702	5,875	1	266	3,275	10,972	16,637	6,024	5,808	5,893	1	284	3,381	10,972	16,637
GScity	6,268	3,707	3,872	1	188	2,200	6,595	11,415	6,024	3,775	3,885	1	195	2,225	6,595	11,415
I(New Bank)	4,866	0.04	0.2	0	0	0	0	1	4,648	0.04	0.2	0	0	0	0	1
I(CU)	4,962	0.02	0.14	0	0	0	0	1	4,741	0.02	0.14	0	0	0	0	1
I(CD)	5,299	0.05	0.21	0	0	0	0	1	5,080	0.05	0.21	0	0	0	0	1

Table 1: continued

(c) Restaurant Ratings – Restaurant-Level Panel

	Full Sample								Matched Sample							
	N	Mean	S.D.	Min	P.25	Median	P.75	Max	N	Mean	S.D.	Min	P.25	Median	P.75	Max
2020 PPP First Draw																
Rating Stars	464,639	3.92	1.29	1	3	4	5	5	432,599	3.93	1.29	1	3	4	5	5
2021 PPP First Draw																
Rating Stars	26,492	4.06	1.25	1	4	5	5	5	25,477	4.06	1.25	1	4	5	5	5

Table 2: Fintech Lenders and Minority-owned Businesses

This table reports the linear probability regression results where the dependent variable is the Fintech loan indicator (0/1). The sample is the linked restaurant-loan-level cross-sectional dataset. The key independent variables are Black, Asian, and Hispanic indicators which are defined as 1 for restaurants with the corresponding ethnic cuisine category. The results of the 2020 and 2021 PPP waves are presented in panels A and B, referring to PPP loans issued during April 2020 and December 2020 and during January 2021 and March 2021, respectively. The full sample and matched sample are indicated through sub-column heads where the matched sample is constructed by matching minority borrowers with non-minority borrowers in the same state, business type (aggregated), food price range, and having an employment size with a difference of up to five employees. In addition to the variables reported in the table, we also control for city and business type fixed effects. Detailed variable definitions are in Appendix Table A1. For demonstration purposes, the dependent variable is multiplied by 100. Standard errors clustered at the city level as reported in the parentheses. * p < 0.10, ** p < 0.05, *** p < 0.01.

(a) Panel A: 2020 PPP

Dep. Var.	I(Fintech) × 100							
Sample	Full Sample				Matched Sample			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
I(Black)	9.17***	8.66***	8.00***	4.99***	9.06***	8.21***	7.64***	4.86***
	(1.63)	(1.62)	(1.59)	(1.67)	(1.65)	(1.65)	(1.64)	(1.71)
I(Asian)	8.44***	7.93***	7.43***	6.07***	8.15***	7.53***	7.08***	5.84***
	(0.41)	(0.4)	(0.38)	(0.4)	(0.41)	(0.4)	(0.38)	(0.4)
I(Hispanic)	1.22***	1.09***	0.88***	0.06	0.87***	0.98***	0.82**	0.04
	(0.33)	(0.32)	(0.32)	(0.32)	(0.33)	(0.33)	(0.32)	(0.33)
Employment		-0.07***	-0.06***	-0.06***		-0.14***	-0.14***	-0.14***
		(0.00)	(0.00)	(0.00)		(0.01)	(0.01)	(0.01)
I(Franchise)			-0.31	-0.23			0.02	-0.16
			(0.32)	(0.34)			(0.36)	(0.38)
City FEs				X				X
Business Type FEs			X	X			X	X
Observations	92,557	92,557	92,556	88,873	86,097	86,097	86,095	82,426
Adjusted R^2	0.013	0.018	0.041	0.062	0.012	0.019	0.042	0.063

(b) Panel B: 2021 PPP

Dep. Var.	I(Fintech) × 100							
Sample	Full Sample				Matched Sample			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
I(Black)	20.92***	20.08***	16.18***	5.52	20.95***	19.85***	16.07***	6.62
	(5.16)	(5.16)	(5.05)	(6.08)	(5.15)	(5.14)	(5.07)	(6.01)
I(Asian)	11.54***	10.70***	10.14***	6.10***	11.20***	10.08***	9.60***	5.67***
	(1.39)	-(1.39)	(1.33)	(1.80)	(1.40)	(1.40)	(1.34)	(1.82)
I(Hispanic)	5.67***	5.48***	4.95***	3.31*	5.50***	5.62***	5.04***	3.71*
	(1.44)	(1.45)	(1.42)	(1.93)	(1.47)	(1.47)	(1.44)	(1.98)
Employment		-0.18***	-0.14***	-0.12***		-0.37***	-0.26***	-0.30***
		(0.03)	(0.03)	(0.05)		(0.05)	(0.05)	(0.07)
I(Franchise)			-2.95*	-7.72***			-2.42	-6.90**
			(1.78)	(2.74)			(1.88)	(2.85)
City FEs				X				X
Business Type FEs			X	X			X	X
Observations	6,268	6,268	6,266	4,150	6,024	6,024	6,022	3,984
Adjusted R^2	0.018	0.022	0.061	0.078	0.017	0.024	0.061	0.085

Table 3: Minority-Non-Minority Rating Gap

This table reports the regression results from examining the difference in ratings between minority and non-minority-owned restaurants that borrow from fintech and non-fintech lenders. The sample is the linked restaurant-loan monthly panel dataset and we calculate the monthly average of the ratings. The sample period of ratings is April 2020 to March 2021 (during the Covid crisis). The dependent variable is the Rating Stars, which ranges from 0 to 5, based on customer ratings from yelp.com. Key independent variables include Black, Asian, and Hispanic indicators that are defined as 1 for restaurants with the corresponding ethnic cuisine category and the Fintech indicator that is defined as 1 for loans backed by fintech lenders. The 2020 and 2021 PPP waves are indicated in column heads, referring to PPP loans issued during April 2020 and December 2020 and during January 2021 and March 2021, respectively. The matched and full samples are indicated through sub-column heads where the matched sample is constructed in the same way as in Table 2. In addition to the variables reported in the table, we also control for city × month (or month) fixed effects, business type fixed effects, and eating policy dummies for delivery, takeout, reservations, and outdoor seating. Detailed variable definitions are in Appendix Table A1. Employment is divided by 100 for demonstration purposes. Standard errors clustered at the restaurant level as reported in the parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Dep. Var.	Rating Stars							
Sample	2020 PPP				2021 PPP			
	Full Sample		Matched Sample		Full Sample		Matched Sample	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
I(Black) × I(Fintech)	-0.25**	-0.23**	-0.24**	-0.23**	-0.14	-0.29	-0.12	-0.26
	(0.11)	(0.11)	(0.11)	(0.11)	(0.18)	(0.21)	(0.18)	(0.21)
I(Asian) × I(Fintech)	-0.06***	-0.04*	-0.06***	-0.04*	-0.02	0.01	-0.00	0.03
	(0.02)	(0.02)	(0.02)	(0.02)	(0.07)	(0.10)	(0.07)	(0.10)
I(Hisp.) × I(Fintech)	-0.02	0	-0.02	-0.01	-0.18**	-0.28**	-0.19**	-0.27**
	(0.03)	(0.03)	(0.03)	(0.03)	(0.09)	(0.13)	(0.09)	(0.13)
I(Fintech)	0.05***	0.04***	0.05***	0.04***	-0.06	-0.01	-0.06	-0.02
	(0.01)	(0.01)	(0.01)	(0.01)	(0.04)	(0.06)	(0.04)	(0.06)
I(Black)	0.05	0.06	0.04	0.05	-0.05	-0.01	-0.05	-0.01
	(0.04)	(0.04)	(0.04)	(0.04)	(0.11)	(0.13)	(0.11)	(0.13)
I(Asian)	-0.03***	-0.03***	-0.04***	-0.04***	-0.04	-0.01	-0.04	-0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.03)	(0.04)	(0.03)	(0.04)
I(Hisp.)	-0.11***	-0.11***	-0.11***	-0.11***	-0.16***	-0.09*	-0.15***	-0.08
	(0.01)	(0.01)	(0.01)	(0.01)	(0.04)	(0.06)	(0.04)	(0.06)
Employment	-0.11***	-0.12***	-0.19***	-0.19***	-0.38***	-0.42**	-0.60***	-0.82***
	(0.01)	(0.01)	(0.02)	(0.02)	(0.10)	(0.18)	(0.12)	(0.19)
I(Franchise)	-1.06***	-1.02***	-1.05***	-1.00***	-0.91***	-0.81***	-0.90***	-0.77***
	(0.01)	(0.01)	(0.02)	(0.02)	(0.07)	(0.1 0)	(0.07)	(0.10)
Monthly FEs	X		X		X		X	
City × Monthly FEs		X		X		X		X
Business Type FEs	X	X	X	X	X	X	X	X
Eating Policy Controls	X	X	X	X	X	X	X	X
Observations	464,639	434,948	432,598	403,363	26,491	14,723	25,476	14,095
Adjusted R^2	0.052	0.072	0.048	0.069	0.041	0.05	0.039	0.047

Table 4: Business Capital and Minority-Non-Minority Rating Gap

This table reports the regression results from examining the impact of business capital on the difference in the minority-non-minority rating gap between fintech and non-fintech lenders. The sample is the linked restaurant-loan monthly panel dataset and we calculate the monthly average of the ratings. The sample period of ratings is April 2020 to March 2021 (during the Covid crisis). The dependent variable is the Rating Stars, which ranges from 0 to 5, based on customer ratings from yelp.com. Business Capital (BC) is proxied by the total number of ratings in the entire period of our analysis (from April 2020 to March 2021). BC is divided by 100 for demonstration purposes and winsorized at the 99% cuts. Black, Asian, and Hispanic indicators are defined as 1 for restaurants with the corresponding ethnic cuisine category. The Fintech indicator is defined as 1 for loans backed by fintech lenders. The 2020 and 2021 PPP waves are indicated in column heads, referring to PPP loans issued during April 2020 and December 2020 and during January 2021 and March 2021, respectively. The matched and full samples are indicated through sub-column heads. The construction of the matched sample and control variables are the same as in Table 3. Detailed variable definitions are in Appendix Table A1. Employment is divided by 100 for demonstration purposes. Standard errors clustered at the restaurant level as reported in the parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Dep. Var.	Rating Stars							
Sample	2020 PPP				2021 PPP			
	Full Sample		Matched Sample		Full Sample		Matched Sample	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
I(Black) × I(FT) × BC	0.03	0.02	0.03	0.03	-0.01	0.00	-0.00	0.04
	(0.13)	(0.11)	(0.13)	(0.11)	(0.08)	(0.12)	(0.09)	(0.12)
I(Asian) × I(FT) × BC	0.07***	0.07***	0.08***	0.07***	0.11**	0.15***	0.12***	0.17***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.04)	(0.05)	(0.04)	(0.05)
I(Hisp.) × I(FT) × BC	0.09***	0.08***	0.09***	0.08***	-0.09	-0.19*	-0.08	-0.18
	(0.02)	(0.02)	(0.02)	(0.02)	(0.08)	(0.11)	(0.08)	(0.11)
I(FT)	-0.01	-0.01	-0.02	-0.01	-0.11***	-0.09*	-0.12***	-0.10*
	(0.01)	(0.01)	(0.01)	(0.01)	(0.03)	(0.05)	(0.03)	(0.05)
I(Black)	0.01	0.03	0	0.01	-0.08	-0.08	-0.08	-0.09
	(0.04)	(0.04)	(0.04)	(0.04)	(0.10)	(0.12)	(0.10)	(0.12)
I(Asian)	-0.04***	-0.04***	-0.05***	-0.05***	-0.05**	-0.03	-0.06**	-0.03
	(0.01)	(0.01)	(0.01)	(0.01)	(0.03)	(0.04)	(0.03)	(0.04)
I(Hispanic)	-0.12***	-0.12***	-0.12***	-0.11***	-0.19***	-0.13**	-0.18***	-0.12**
	(0.01)	(0.01)	(0.01)	(0.01)	(0.03)	(0.05)	(0.03)	(0.05)
Employment	-0.11***	-0.12***	-0.19***	-0.20***	-0.38***	-0.43**	-0.61***	-0.84***
	(0.01)	(0.01)	(0.02)	(0.02)	(0.10)	(0.19)	(0.13)	(0.19)
I(Franchise)	-1.06***	-1.02***	-1.05***	-1.00***	-0.92***	-0.82***	-0.90***	-0.78***
	(0.01)	(0.01)	(0.02)	(0.02)	(0.07)	(0.10)	(0.07)	(0.10)
Monthly FEs	X		X		X		X	
City × Monthly FEs		X		X		X		X
Other Controls	X	X	X	X	X	X	X	X
Observations	464,639	434,948	432,598	403,363	26,491	14,723	25,476	14,095
Adjusted R^2	0.052	0.072	0.049	0.069	0.041	0.05	0.04	0.048

Table 5: Relative Geographic Lending Scope and Minority-Non-Minority Rating Gap

This table reports the regression results from examining the impact of business capital on the difference in the minority-non-minority rating gap between fintech and non-fintech lenders. The sample is the linked restaurant-loan monthly panel dataset and we calculate the monthly average of the ratings. The sample period of ratings is April 2020 to March 2021 (during the Covid crisis). The dependent variable is the Rating Stars, which ranges from 0 to 5, based on customer ratings from yelp.com. Relative geographic lending scope (GSr) is calculated as the ratio of the total number of zip codes to the total number of cities the lender covers in the entire PPP sample. Black, Asian, and Hispanic indicators are defined as 1 for restaurants with the corresponding ethnic cuisine category. The Fintech indicator is defined as 1 for loans backed by fintech lenders. The 2020 and 2021 PPP waves are indicated in column heads, referring to PPP loans issued during April 2020 and December 2020 and during January 2021 and March 2021, respectively. The matched and full samples are indicated through sub-column heads. The construction of the matched sample and control variables are the same as in Table 3. Detailed variable definitions are in Appendix Table A1. CDFIs and CDCs are excluded because their lending scope may be restricted to certain communities. Employment is divided by 100 for demonstration purposes. Standard errors clustered at the restaurant level as reported in the parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Dep. Var.	Rating Stars							
Sample	2020 PPP				2021 PPP			
	Full Sample		Matched Sample		Full Sample		Matched Sample	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
I(Black)×I(FT)×GS_r	-0.16**	-0.15**	-0.15**	-0.15**	-0.08	-0.18	-0.07	-0.17
	(0.07)	(0.07)	(0.07)	(0.07)	(0.12)	(0.14)	(0.12)	(0.15)
I(Asian)×I(FT)×GS_r	-0.04***	-0.03*	-0.04***	-0.03**	-0.01	0.01	0	0.02
	(0.01)	(0.01)	(0.01)	(0.01)	(0.04)	(0.06)	(0.04)	(0.06)
I(Hisp.)×I(FT)×GS_r	-0.01	0	-0.01	0	-0.12**	-0.19**	-0.12**	-0.18**
	(0.02)	(0.02)	(0.02)	(0.02)	(0.06)	(0.09)	(0.06)	(0.09)
I(FT)	0.05***	0.04***	0.05***	0.04***	-0.05	-0.01	-0.06	-0.02
	(0.01)	(0.01)	(0.01)	(0.01)	(0.04)	(0.06)	(0.04)	(0.06)
I(Black)	0.04	0.06	0.03	0.04	-0.07	-0.02	-0.06	-0.02
	(0.04)	(0.04)	(0.04)	(0.04)	(0.12)	(0.14)	(0.12)	(0.14)
I(Asian)	-0.03***	-0.03***	-0.04***	-0.04***	-0.03	0	-0.04	-0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.03)	(0.04)	(0.03)	(0.04)
I(Hispanic)	-0.11***	-0.11***	-0.11***	-0.11***	-0.16***	-0.10*	-0.15***	-0.09
	(0.01)	(0.01)	(0.01)	(0.01)	(0.04)	(0.06)	(0.04)	(0.06)
Employment	-0.11***	-0.11***	-0.19***	-0.19***	-0.39***	-0.43**	-0.60***	-0.81***
	(0.01)	(0.01)	(0.02)	(0.02)	(0.1)	(0.19)	(0.13)	(0.19)
I(Franchise)	-1.06***	-1.02***	-1.05***	-1.00***	-0.91***	-0.81***	-0.90***	-0.77***
	(0.01)	(0.02)	(0.02)	(0.02)	(0.07)	(0.10)	(0.07)	(0.10)
Monthly FEs	X		X		X		X	
City × Monthly FEs		X		X		X		X
Other Controls	X	X	X	X	X	X	X	X
Observations	461,493	431,821	429,480	400,262	26,025	14,342	25,036	13,745
Adjusted R^2	0.052	0.072	0.049	0.069	0.041	0.05	0.039	0.047

Table 6: Previous Lending Relationships

This table reports the regression results from examining the difference in previous lending relationships between minority and non-minority-owned restaurants and how previous lending relationships affect fintech usage. The sample is the linked restaurant-loan-level cross-sectional dataset. Panels A and B report the regression results where the dependent variable is I(Relationships), a dummy variable that equals 1 if the borrower had SBA 7(a) or 504 loans during 2009-2019, on the 2020 and 2021 PPP waves respectively. Panels C and D report the regression results where the dependent variable is the Fintech loan indicator (0/1) on the 2020 and 2021 PPP waves respectively. The 2020 and 2021 PPP waves refer to April 2020 to December 2020 and January 2021 to March 2021. Black, Asian, and Hispanic indicators are defined as 1 for restaurants with the corresponding ethnic cuisine category. The matched and full samples are indicated through sub-column heads. The construction of the matched sample and control variables are the same as in Table 2. Detailed variable definitions are in Appendix Table A1. For demonstration purposes, dependent variables are multiplied by 100. Standard errors clustered at the city level as reported in the parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

(a) Panel A: Minority Owned and Lending Relationships (2020 PPP)

Dep. Var.	I(Relationships) × 100							
Sample	Full Sample				Matched Sample			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
I(Black)	-1.56**	-1.48**	-0.92	-1.02	-1.49**	-1.30*	-0.76	-0.87
	(0.66)	(0.66)	(0.66)	(0.68)	(0.67)	(0.67)	(0.66)	(0.68)
I(Asian)	-1.57***	-1.50***	-0.78***	-1.04***	-1.58***	-1.45***	-0.72***	-1.00***
	(0.16)	(0.16)	(0.16)	(0.18)	(0.17)	(0.16)	(0.16)	(0.18)
I(Hispanic)	-1.64***	-1.63***	-1.05***	-0.98***	-1.68***	-1.70***	-1.11***	-1.03***
	(0.15)	(0.15)	(0.15)	(0.17)	(0.15)	(0.15)	(0.15)	(0.17)
Employment		0.98***	0.63***	0.52**		3.18***	2.34***	2.11***
		(0.2)	(0.2)	(0.21)		(0.44)	(0.43)	(0.45)
I(Franchise)			3.84***	3.80***			3.87***	3.83***
			(0.28)	(0.3)			(0.29)	(0.31)
City FEs				X				X
Business Type FEs			X	X			X	X
Observations	92,557	92,557	92,556	88,873	86,097	86,097	86,095	82,426
Adjusted R^2	0.002	0.002	0.011	0.008	0.002	0.003	0.011	0.008

(b) Panel B: Minority-Owned and Lending Relationships (2021 PPP)

Dep. Var.	I(Relationships) × 100							
Sample	Full Sample				Matched Sample			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
I(Black)	0.47	0.61	0.72	1.89	0.47	0.59	0.71	1.89
	(1.68)	(1.68)	(1.69)	(2.31)	(1.7)	(1.7)	(1.71)	(2.35)
I(Asian)	-0.88**	-0.74**	-0.45	-0.05	-0.90**	-0.78**	-0.47	-0.07
	(0.36)	(0.37)	(0.4)	(0.56)	(0.36)	(0.37)	(0.4)	(0.57)
I(Hispanic)	-0.85*	-0.82*	-0.65	0.05	-0.87**	-0.88**	-0.69	-0.02
	(0.43)	(0.43)	(0.44)	(0.66)	(0.44)	(0.44)	(0.45)	(0.67)
Employment		2.98	2.51	2.03		4.10**	3.4	4.95
		(2.06)	(2.05)	(1.61)		(2.06)	(2.13)	(3.34)
I(Franchise)			1.45	1.47			1.43	1.61
			(0.93)	(1.19)			(0.99)	(1.25)
City FEs				X				X
Business Type FEs			X	X			X	X
Observations	6,268	6,268	6,266	4,150	6,024	6,024	6,022	3,984
Adjusted R^2	0.001	0.002	0.005	0.013	0.001	0.001	0.005	-0.01

Table 6: continued

(c) Panel C: Lending Relationships and Fintech Usage (2020 PPP)

Dep. Var.	I(Fintech) × 100							
Sample	Full Sample				Matched Sample			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
I(Relationships)	-0.06***	-0.06***	-0.06***	-0.05***	-0.07***	-0.06***	-0.06***	-0.05***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)
I(Black)			7.95***	4.94***			7.60***	4.81***
			(1.6)	(1.67)			(1.64)	(1.72)
I(Asian)			7.39***	6.02***			7.04***	5.79***
			(0.38)	(0.4)			(0.38)	(0.4)
I(Hispanic)			0.82***	0.01			0.75**	-0.02
			(0.32)	(0.32)			(0.32)	(0.33)
Employment		-7.18***	-6.41***	-6.47***		-15.43***	-13.98***	-13.63***
		(0.32)	(0.3)	(0.3)		(0.89)	(0.83)	(0.8)
I(Franchise)		-1.49***	-0.09	-0.04		-1.14***	0.23	0.03
		(0.32)	(0.32)	(0.34)		(0.36)	(0.36)	(0.38)
City FEs				X				X
Business Type FEs			X	X			X	X
Observations	92,557	92,556	92,556	88,873	86,097	86,095	86,095	82,426
Adjusted R^2	0.002	0.032	0.042	0.062	0.002	0.035	0.043	0.063

(d) Panel D: Lending Relationships and Fintech Usage (2021 PPP)

Dep. Var.	I(Fintech) × 100							
Sample	Full Sample				Matched Sample			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
I(Relationships)	-0.18***	-0.15***	-0.15***	-0.11***	-0.18***	-0.16***	-0.15***	-0.10***
	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)	(0.02)
I(Black)			16.28***	5.73			16.18***	6.81
			(5.04)	(6.07)			(5.05)	(6)
I(Asian)			10.07***	6.09***			9.52***	5.66***
			(1.33)	(1.8)			(1.34)	(1.82)
I(Hispanic)			4.85***	3.32*			4.93***	3.71*
			(1.42)	(1.93)			(1.44)	(1.98)
Employment		-17.23***	-13.24***	-12.16**		-31.37***	-25.76***	-29.09***
		(3.35)	(3.13)	(4.72)		(5.34)	(5.25)	(7.23)
I(Franchise)		-4.73***	-2.74	-7.56***		-4.20**	-2.21	-6.73**
		(1.8)	(1.78)	(2.74)		(1.89)	(1.88)	(2.85)
City FEs				X				X
Business Type FEs			X	X			X	X
Observations	6,268	6,266	6,266	4,150	6,024	6,022	6,022	3,984
Adjusted R^2	0.003	0.051	0.063	0.079	0.003	0.052	0.063	0.085

Table 7: First-Time Banks

This table reports the regression results of restaurants that borrow from lenders who are banks that participate in SBA programs for the first time and from lenders who had previously participated in SBA programs. The sample is the linked restaurant-loan-level cross-sectional dataset (Panel A) and the linked restaurant-loan monthly panel dataset (Panel B). The sample period of ratings in Panel B is April 2020 to March 2021 (during the Covid crisis). In Panel A, the dependent variable is the New Bank loan indicator (0/1) that equals one if the lender is a first-time bank in SBA programs. In Panel B, the dependent variable is the Rating Stars, which ranges from 0 to 5, based on customer ratings from yelp.com. We use the SBA 7(a) and 504 loan-level data from 1990-2019 to identify lenders that participated in SBA programs before. The 2020 and 2021 PPP waves are indicated in column heads. The matched and full samples are indicated through sub-column heads. Other variable definitions, the construction of the matched sample, and control variables are the same as in Table 2 (Panel A) and Table 3 (Panel B). Detailed variable definitions are in Appendix Table A1. Fintech lenders and non-banks are excluded. Standard errors clustered at the city level (Panel A) and the restaurant level (Panel B), as reported in the parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

(a) Panel A: First-Time Banks Usage

Dep. Var.	I(New Bank) × 100							
Sample	2020 PPP				2021 PPP			
	Full Sample		Matched Sample		Full Sample		Matched Sample	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
I(Black)	-0.63	0.2	-0.54	0.44	5.31	7.54	5.13	7.36
	-0.92	-0.93	-0.94	-0.96	-6.32	-7.76	-6.43	-7.87
I(Asian)	-2.23***	-1.40***	-2.21***	-1.39***	-2.54***	-1.82**	-2.48***	-1.84**
	-0.21	-0.21	-0.21	-0.21	-0.71	-0.79	-0.71	-0.83
I(Hispanic)	-0.4	-0.12	-0.45*	-0.17	1.11	1.98	0.99	2.09
	-0.25	-0.24	-0.25	-0.25	-1.05	-1.53	-1.06	-1.58
Employment	-0.01***	-0.01***	0	0	0.01	-0.01	0.03	-0.02
	0	0	0	0	-0.02	-0.02	-0.04	-0.04
I(Franchise)	-0.42	-0.07	-0.35	-0.09	-1.13	0.77	-1.26	0.6
	-0.26	-0.27	-0.29	-0.3	-1.07	-1.67	-1.13	-1.78
City FEs		X		X		X		X
Business Type FEs	X	X	X	X	X	X	X	X
Observations	82,285	78,589	76,080	72,390	4,865	2,950	4,647	2,815
Adjusted R^2	0.002	0.132	0.002	0.133	0.005	0.098	0.004	0.094

(b) Panel B: Rating Gap

Dep. Var.	Rating Stars							
Sample	2020 PPP				2021 PPP			
	Full Sample		Matched Sample		Full Sample		Matched Sample	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
I(Black) × I(New Bank)	0.09	0.07	0.09	0.05	0.44*	0.3	0.41*	0.31
	-0.15	-0.19	-0.14	-0.19	-0.24	-0.31	-0.24	-0.31
I(Asian) × I(New Bank)	-0.02	-0.02	-0.02	-0.02	-0.06	0.14	-0.09	0.07
	-0.04	-0.05	-0.04	-0.05	-0.16	-0.35	-0.16	-0.37
I(Hisp.) × I(New Bank)	0.03	0.02	0.02	0.01	-0.25	-0.32	-0.28	-0.37
	-0.04	-0.05	-0.04	-0.05	-0.18	-0.32	-0.18	-0.33
I(New Bank)	0	0	0	0.01	0.19***	0.24*	0.22***	0.27*
	-0.02	-0.02	-0.02	-0.02	-0.07	-0.13	-0.07	-0.14
Monthly FEs	X		X		X		X	
City × Monthly FEs		X		X		X		X
Other Controls	X	X	X	X	X	X	X	X
Observations	411,222	381,574	380,498	351,392	20,145	10,090	19,275	9,592
Adjusted R^2	0.052	0.073	0.049	0.069	0.043	0.051	0.04	0.049

Table 8: Non-Federally Insured Lenders

This table reports the regression results of restaurants that borrow from lenders who are not federally insured. The sample is the linked restaurant-loan-level cross-sectional dataset (Panel A) and the linked restaurant-loan monthly panel dataset (Panel B). The sample period of ratings in Panel B is April 2020 to March 2021 (during the Covid crisis). In Panel A, the dependent variable is the Uninsured loan indicator (0/1) that equals one if the lender is not federally insured. In Panel B, the dependent variable is the Rating Stars, which ranges from 0 to 5, based on customer ratings from yelp.com. We use the FFEIC data to identify whether the lender is federally insured or not. The 2020 and 2021 PPP waves are indicated in column heads. The matched and full samples are indicated through sub-column heads. Other variable definitions, the construction of the matched sample, and control variables are the same as in Table 2 (Panel A) and Table 3 (Panel B). Detailed variable definitions are in Appendix Table A1. Fintech lenders and non-banks are excluded. Standard errors clustered at the city level (Panel A) and the restaurant level (Panel B) as reported in the parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

(a) Panel A: Non-Federally Insured Lender Usage

Dep. Var.	I(Uninsured) × 100							
Sample	2020 PPP				2021 PPP			
	Full Sample		Matched Sample		Full Sample		Matched Sample	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
I(Black)	1.00*	0.7	0.99*	0.7	-0.64***	-0.62	-0.62***	-0.66
	(0.58)	(0.56)	(0.59)	(0.57)	(0.22)	(0.54)	(0.23)	(0.56)
I(Asian)	0.27***	0.26**	0.22**	0.20*	2.21***	0.88	2.27***	0.9
	(0.1)	(0.11)	(0.1)	(0.11)	(0.57)	(0.7)	(0.58)	(0.72)
I(Hispanic)	-0.03	0.02	-0.05	0.01	-0.26	-0.64	-0.21	-0.57
	(0.08)	(0.08)	(0.08)	(0.08)	(0.32)	(0.46)	(0.32)	(0.47)
Employment	-0.00***	-0.00***	-0.01***	-0.00***	0	-0.01*	0	-0.03**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)	(0.02)	(0.01)
I(Franchise)	-0.41***	-0.27***	-0.43***	-0.29***	-0.55*	-1.77***	-0.47	-1.79**
	(0.06)	(0.06)	(0.07)	(0.07)	(0.32)	(0.66)	(0.32)	(0.7)
City FEs		X		X		X		X
Business Type FEs	X	X	X	X	X	X	X	X
Observations	85,349	81,702	79,145	75,502	5,298	3,321	5,079	3,184
Adjusted R^2	0.001	0.053	0.001	0.052	0.008	0.039	0.009	0.039

(b) Panel B: Rating Gap

Dep. Var.	Rating Stars							
Sample	2020 PPP				2021 PPP			
	Full Sample		Matched Sample		Full Sample		Matched Sample	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
I(Black) × I(Uninsured)	-0.16	-0.24	-0.14	-0.23	-	-	-	-
	(0.3)	(0.27)	(0.3)	(0.27)				
I(Asian) × I(Uninsured)	-0.08	-0.08	-0.07	-0.08	-0.16	-0.18	-0.2	-0.18
	(0.09)	(0.1)	(0.09)	(0.1)	(0.2)	(0.37)	(0.2)	(0.38)
I(Hisp.) × I(Uninsured)	-0.09	-0.02	-0.09	-0.03	0.59***	0.12	0.52***	0.12
	(0.16)	(0.17)	(0.16)	(0.17)	(0.15)	(0.34)	(0.15)	(0.34)
I(Uninsured)	-0.05	-0.04	-0.06	-0.04	-0.05	0.2	0	0.2
	(0.06)	(0.07)	(0.06)	(0.07)	(0.14)	(0.32)	(0.13)	(0.32)
Monthly FEs	X		X		X		X	
City × Monthly FEs		X		X		X		X
Other Controls	X	X	X	X	X	X	X	X
Observations	427,705	398,417	396,912	368,112	21,815	11,194	20,931	10,694
Adjusted R^2	0.052	0.073	0.048	0.069	0.04	0.041	0.038	0.036

Table 9: Approval Date

This table reports the regression results from examining the difference in PPP loan approval dates between minority and non-minority-owned restaurants that borrow from fintech and non-fintech lenders. The sample is the linked restaurant-loan-level cross-sectional dataset. The dependent variable, Δ(Approval Date-PPP Starting Date), is the difference between the PPP loan approval date and PPP starting date. The starting date is April 09, 2020, for the 2020 wave and Jan 12, 2021, for the 2021 wave. The 2020 and 2021 PPP waves are indicated in column heads. The matched and full samples are indicated through sub-column heads. Black, Asian, and Hispanic indicators are defined as 1 for restaurants with the corresponding ethnic cuisine category. The Fintech indicator is defined to be 1 for loans backed by fintech lenders. The construction of the matched sample and control variables are the same as in Table 2. Detailed variable definitions are in Appendix Table A1. Standard errors clustered at the city level as reported in the parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Dep. Var.	Δ(Approval Date PPP Starting Date)							
Sample	2020 PPP				2021 PPP			
	Full Sample		Matched Sample		Full Sample		Matched Sample	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
I(Black) × I(Fintech)	-2	-1.49	-2	-1.4	-3.61	-0.01	-3.82	-0.04
	(3.15)	(3.29)	(3.14)	(3.29)	(4.13)	(4.65)	(4.14)	(4.69)
I(Asian) × I(Fintech)	3.45***	3.68***	3.63***	3.88***	-8.11***	-7.34***	-8.20***	-7.54***
	(0.73)	(0.76)	(0.74)	(0.77)	(1.57)	-(2.16)	(1.58)	(2.17)
I(Hispanic) × I(Fintech)	1.41	0.55	1.43	0.61	-8.72***	-6.71**	-8.75***	-6.83**
	(1.12)	(1.16)	(1.12)	(1.16)	(2.04)	(2.64)	(2.06)	(2.68)
I(Fintech)	12.10***	10.72***	11.61***	10.20***	2.42**	0.66	2.38**	0.5
	(0.46)	(0.5)	(0.47)	(0.51)	(0.94)	(1.28)	(0.96)	(1.3)
I(Black)	7.63***	6.30***	7.12***	5.75***	8.71***	4.35	8.91***	4.56
	(1.26)	(1.31)	(1.27)	(1.33)	(2.65)	(2.98)	(2.72)	(3.06)
I(Asian)	8.60***	7.88***	8.12***	7.42***	2.43***	1.42	2.29***	1.28
	(0.3)	(0.32)	(0.3)	(0.32)	(0.77)	(1.09)	(0.78)	(1.1)
I(Hispanic)	4.56***	4.33***	4.44***	4.22***	3.15***	2.51*	3.18***	2.50*
	(0.28)	(0.3)	(0.29)	(0.3)	(0.89)	(1.3)	(0.9)	(1.33)
Employment	-0.08***	-0.08***	-0.18***	-0.18***	-0.05**	-0.05	-0.12***	-0.14***
	(0.00)	(0.00)	(0.01)	(0.01)	(0.02)	(0.04)	(0.03)	(0.04)
I(Franchise)	-7.22***	-7.24***	-7.02***	-7.15***	1.21	0.92	1.62	1.84
	(0.23)	(0.25)	(0.25)	(0.27)	(1.14)	(1.59)	(1.19)	-(1.61)
City FEs		X		X		X		X
Business Type FEs	X	X	X	X	X	X	X	X
Observations	81687	78026	76850	73244	6,266	4,150	6,022	3,984
Adjusted R^2	0.114	0.135	0.117	0.137	0.03	0.036	0.019	0.025

Table 10: Borrower-Lender Features and Matching Probability

This table reports the probit regression results on the probability of being matched for a given borrower lender pair in the PPP. The sample is all potential borrower-lender pairs where we identify feasible lenders as those who lend loans in the city of the borrower according to the entire PPP dataset. The dependent variable is a dummy variable that equals one if the borrower borrows from the lender in the PPP. I(Relationships) is a dummy that equals one if the borrower previously borrowed a SBA 7(a) or 504 loan from the lender during 2009-2019. Geo. Distance is the miles between the zip code regions of the borrower and lender pair. We set the distance to zero when the lender is a fintech lender. Rating is the average of ratings during the period from April 2020 to March 2021 (during the Covid crisis) used in Table 3. N. Loans is the number of loans processed by the lender in the entire PPP and winsorized at 99%. Other variables are generated using the linked restaurant-loan-level cross-sectional dataset and as the same in Table 2. The results of the 2020 and 2021 PPP waves are presented in panels A and B, referring to PPP loans issued during April 2020 and December 2020 and during January 2021 and March 2021, respectively. Detailed variable definitions are in Appendix Table A1. For demonstration purposes, Geo. Distance is divided by 10^3, Employment is divided by 100, and N. Loans is divided by 10^6. Standard errors clustered at the city level as reported in the parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

(a) Panel A: Matching Probability (2020 PPP)

	(1) match	(2) match	(3) match	(4) match	(5) match	(6) match
$I(\text{Relationships})_{lender,borrower}$	2.34***				2.30***	2.27***
	(0.02)				(0.02)	(0.02)
Geo. $\text{Distance}_{lender,borrower}$		-0.15***			-0.17***	-0.33***
		(0.00)			(0.00)	(0.00)
$I(\text{Fintech})_{lender} \times I(\text{Minority})_{borrower}$			0.25***		0.24***	0.25***
			(0.01)		(0.01)	(0.01)
$I(\text{Fintech})_{lender} \times \text{Rating}_{borrower}$				0.02***	0.01**	0.01**
				0	0	0
$I(\text{Minority})_{borrower}$			-0.13***		-0.11***	-0.12***
			0		0	0
$I(\text{Fintech})_{lender}$			-0.20***	-0.17***	-0.33***	-0.35***
			(0.01)	(0.02)	(0.02)	(0.02)
$\text{Rating}_{borrower}$				-0.01***	-0.00***	-0.00**
				0	0	0
$\text{Employment}_{borrower}$						-0.07***
						0
N. Loans_{lender}						3.67***
						(0.02)
Observations	3,864,727	3,864,727	3,864,727	3,864,727	3,864,727	3,864,727
Pseudo R^2	0.019	0.006	0.003	0.001	0.028	0.07

Table 10: continued

(b) Panel B: Matching Probability (2021 PPP)

	(1) match	(2) match	(3) match	(4) match	(5) match	(6) match
$I(\text{Relationships})_{lender,borrower}$	2.23***				2.22***	2.17***
	(0.10)				(0.10)	(0.10)
Geo. $\text{Distance}_{lender,borrower}$		-0.19***			-0.17***	-0.28***
		(0.01)			(0.01)	(0.01)
$I(\text{Fintech})_{lender} \times I(\text{Minority})_{borrower}$			0.26***		0.25***	0.26***
			(0.03)		(0.03)	(0.03)
$I(\text{Fintech})_{lender} \times \text{Rating}_{borrower}$				-0.04**	-0.03**	-0.04**
				(0.02)	(0.02)	(0.02)
$I(\text{Minority})_{borrower}$			-0.16***		-0.15***	-0.16***
			(0.01)		(0.01)	(0.01)
$I(\text{Fintech})_{lender}$			0.08***	0.35***	0.12*	0.13*
			(0.02)	(0.06)	(0.07)	(0.07)
$\text{Rating}_{borrower}$				0.01**	0.01	0.01*
				(0.01)	(0.01)	(0.01)
$\text{Employment}_{borrower}$						0.03
						(0.04)
N. Loans_{lender}						3.24***
						(0.08)
Observations	252,345	252,345	252,345	252,345	252,345	252,345
Pseudo R^2	0.009	0.009	0.006	0.003	0.021	0.051

Table 11: Structural Estimation of the Matching Model

This table reports the estimation results using the Fox (2018) model. The sample is all potential borrower-lender pairs where we identify feasible lenders as those who lend loans in the city of the borrower according to the entire PPP dataset. Due to computational limitation, we restrict to the sample of the New York state. All borrower and lender-specific characteristics are demeaned. I(Fitench) is a dummy that equals one if the lender is a fintech lender. I(Minority) is a dummy that equals one if the borrower is a minority borrower. I(Relationships) is a dummy that equals one if the borrower previously borrowed a SBA 7(a) or 504 loan from the lender during 2009-2019. Rating is the average of ratings during the period from April 2020 to March 2021 (during the Covid crisis) used in Table 3. Geo. Distance is the miles between the zip code regions of the borrower and lender pair. The results of the 2020 and 2021 PPP waves are presented in columns (1) and (2), referring to PPP loans issued during April 2020 and December 2020 and during January 2021 and March 2021, respectively. Detailed variable definitions are in Appendix Table A1. The coefficient on the Geo. Distance is normalized to provide scale for the other coefficients. N. of Inequalities is the total number of inequalities considered. % Satisfied is the fraction of matches satisfying pairwise stable using the vector of parameter estimates. I(Relationships) v.s Fin-Minority reports the ratio of the coefficients on $I(\text{Relationships})_{lender,borrower}$ to $I(\text{Fintech})_{lender} \times I(\text{Minority})_{borrower}$.

	(1) 2020 PPP	(2) 2021 PPP
$I(\text{Fintech})_{lender} \times I(\text{Minority})_{borrower}$	262.14	141.73
$I(\text{Relationships})_{lender,borrower}$	381.18	290.02
$I(\text{Fintech})_{lender} \times \text{Rating}_{borrower}$	-3.19	-7.43
Geo. $\text{Distance}_{lender,borrower}$	-1	-1
N. of Inequalities	9,372,434	101,686
% Satisfied	63.26%	59.72%
I(Relationships) v.s Fin-Minority	1.45	2.05